In Search of Working Time?

Hours Constraints, Firms and Mobility[*]

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Abstract

Can workers reach their ideal working hours over time? This paper provides novel empirical evidence on hours constraints—barriers for workers to work their desired hours at a given wage rate—by linking self-reported hour preferences from large-scale survey data with administrative employer-employee data between 2003 and 2023. Twenty percent of French salaried workers report wanting to increase their hours at their given wage. Leveraging the panel dimension of my data, I show that constrained workers switch employers more frequently and experience increases in hours and earnings through mobility. However, most constrained workers remain unable to adjust their hours to their desired level within 3 years after their report. Next, I develop a revealed preference method to quantify welfare effects associated with constraints and find that workers would on average accept a 10.2% reduction in hourly wages to work in a job offering their desired number of hours. These findings highlight the important role of hours worked as a job amenity in shaping labor market sorting.

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1   Introduction

Both a source of income and disutility, working hours are a central element of workers' lives. However, most workers cannot freely choose their hours, as first emphasized by Lewis (1967), since employers have a clear interest in the hours worked by their employees. This implies that several workers may be *constrained* in jobs where they cannot work their desired number of hours. When unable to choose their hours within their current job, a crucial question is whether they can, and at what cost, relax their hours constraints.

This paper provides novel empirical evidence on the topic of hours constraints. Combining self-reported hours preferences from the French Labour Force Survey with panel employer-employee data, I can track workers after their report and observe their adjustments in hours and earnings over a large number of years. Using this unique data, I quantify welfare effects associated with constraints, i.e. how much workers would agree to lose (in hourly wage) to reach their optimal hours. The richness of my data also allows me to document several unexplored aspects of hours constraints, e.g. which workers are most able to close the gap to desired hours or what type of labor market mobility favor adjustments in hours for constrained workers.

Hours constraints have received significant attention in the labor literature (see Kahn and Lang (2001) for an introduction). Empirical studies consistently find that a large proportion of workers are not working their desired hours, although the direction of constraints varies across countries. Jarosch et al. (2025) show in a recent paper that German and British workers tend to be *overworked*, or constrained from below, while US workers are mostly *underworked* or constrained from above. In the German case, more than two thirds of workers report wanting to work fewer hours. France exhibits a pattern closer to the US: evidence from the *Enquête Emploi*, the French Labour Force Survey, indicates that 20% of salaried workers would work more hours at their given wage rate, compared to 40% in the US (based on the RPS survey). Such magnitude points to hours constraints as a widespread labor market phenomenon.

A first question concerns the origins of constraints: what prevents workers from working their desired hours? Working hours are heavily regulated, particularly in France[1], which implies that employers may have to bear additional (overtime) costs to increase hours of their employees. This restriction yet does not apply to the frontier between part-time and full-time work, which is at the heart of this paper. Early research on the topic (Altonji and Paxson, 1986; Dickens and Lund-

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[1]See Breda et al. (2025) for more on the French working time regulation.

berg, 1993) rather emphasized the importance of occupation in hours practices. Certain jobs, e.g. train drivers or school teachers, are associated with specific hours requirements that may leave little room for adjustment. However, recent work has rather focused on the role of firm-specific features, following the idea that hours worked likely depend on each firm's organization and technology. Kahn and Lang (2001) provide a broad discussion of the potential sources of firms' preferences over hours, e.g. highlighting the role played by coordination in team production contexts, as in Rosen (1986). Labanca and Pozzoli (2023) build on this idea to rationalize hours constraints as compensated by wage differentials arising from productivity gains. Another argument connects hours constraints to monopsony power (Manning, 2003), in that firms may be able and have an interest in keeping some of their workers underemployed to freely adjust their hours when the activity fluctuates (Bell and Blanchflower, 2021). Lachowska et al. (2023) includes the most comprehensive theoretical framework to date for the study of constraints, using an extension of the Lewis-Rosen model (Lewis, 1969; Rosen, 1974) under imperfect competition. Their findings point to the existence of a job ladder on wages and hours, i.e. a hierarchical ranking of employers based on job desirability, as the source of hours constraints, and conclude that long-hour jobs are too costly for most employers.

A second question concerns the welfare implications of constraints. Survey data suggest the distance to desired hours may be large, particularly for part-time workers who mostly want to increase their hours to a full-time schedule. This implies that constrained workers may be far from their labor supply curve and would accept a large wage reduction to close the gap. Lachowska et al. (2023) take a revealed preference approach to estimate this gap and find that workers would on average require a 12% higher wage to be as well off as they would be while working their ideal hours. They also find a 15% average distance between actual and desired hours, consistent with survey data. Their methodology reflects the magnitude of welfare effects associated with constraints at the labor market level, but it does not rely on actual moves of workers who are in a constrained situation.

The lack of suitable data have made it difficult to address these questions. Preferences over hours are hard to identify, and aside from a few exceptions (Labanca and Pozzoli (2023) use a firm-level proxy based on the within-firm dispersion of hours, while Lachowska et al. (2023) take an aggregate approach relying on firms' estimated value and hours policies), the most common approach relies on surveys. However, surveys that directly elicit hours preferences are generally not panel data, with the notable exception of the data used in Jarosch et al. (2025), and are

rarely linked to firm-level information. Moreover, their measures of hours and earnings are likely imperfect, as they typically rely on self-reported data rather than administrative records.

In this paper, I overcome previous data limitations by linking self-reported hour preferences from a large-scale survey with panel employer-employee data. I exploit the presence of establishments' identifiers in the French Labour Force Survey, conducted by Insee[2], and use them to link survey data to administrative records. As there are no common individual identifiers between both sources, I adopt a "1-to-1" matching approach based on variables such as age, gender or birth department combined with the firm identifier. This method allows me to retain information for a majority of surveyed salaried workers (67%, 435,472 individuals) between 2003 and 2023, capturing their self-reported hour preferences over six quarters and their administrative job characteristics, including paid hours and labor earnings, over a large number of years. By exploiting the panel structure of the administrative data, I can study the labor market trajectories of constrained workers and examine the welfare effects associated with their job changes. This unique linkage extends beyond the scope of hours constraints and contributes to bridging survey and administrative sources for economic research. The paper is then organized in three steps.

The first step examines the employment context of workers who report hours constraints to improve our understanding of the phenomenon. Hours-constrained workers are concentrated at the bottom of the (hourly) wage distribution and primarily seek to increase earnings through additional work. This is especially the case for involuntary part-time workers, who report being unable to switch to a full-time schedule and are constrained in particular low-wage jobs. On the other hand, full-time constrained workers work a similar number of hours than unconstrained workers and seem to mostly differ in terms of preferences rather than working conditions. Occupational sorting emerges as a major factor for involuntary part-time work, as concerned workers are heavily concentrated in few low-wage occupations notoriously intensive in part-time jobs. Firm sorting also plays an important role: evidence shows strong homogeneity in hours within firms but large heterogeneity between firms, even within a given occupation. Using an AKM (Abowd et al., 1999) decomposition to identify firm effects in both hours and wages, I find that constrained workers are overrepresented in firms offering low hours and low wages, consistent with the existence of a job ladder. Tackling the heterogeneity in hours inside of firms, I show evidence of worker segmentation over access to full-time jobs associated with gender and experience.

The second part of the paper provides the first dynamic study of hours constraints at the

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[2]The French National Institute for Statistics and Economic Studies.

worker-level. Leveraging the panel dimension of my data, I track the labor market trajectories of constrained workers in the years following their survey responses. I find that workers who want to increase their hours are more likely to switch employers shortly after their report. Using an event-study design, I estimate that constrained part-time workers increase their hours and earnings through mobility respectively by 6.3% and 5.5% as compared to prior unconstrained workers. This corresponds respectively to a 8.7% and 3.9% increase as compared to non-movers. Conversely, estimates are close to zero in the full-time group, showing that the experience of hours constraints likely differs across both types. The richness of my data also allows me to provide a thorough description of adjustment mechanisms. Workers are more likely to adjust their hours by switching occupation or moving to firms with long-hour policies, consistent with the prior identified role of occupational and firm rigidities. Despite evidence of large changes in hours, most constrained workers are not able to reach their desired hours by 3 years after their report.

The third step develops a method to quantify workers' willingness to pay (WTP) for their desired working hours, i.e. how much income they would sacrifice to work their optimal hours, building on the approach of Le Barbanchon et al. (2020) on the relation between wage and commute. The method takes advantage of workers' self-reported desired hours and of their subsequent employer-to-employer transitions. Workers start in an initial job with a given wage and hours, then report their desired hours at that wage (as in the Labour Force Survey). I estimate the parameters of their utility function by finding the iso-utility curve that best explains which destination jobs they accept. Specifically, the method identifies the curve that minimizes the distance between accepted jobs that provide lower utility than the initial job and their projection onto that curve, as in Le Barbanchon et al. (2020). I solve the optimization problem using a grid search algorithm and find an average WTP equal to 10.2% of workers' current wage. The estimate is in the same magnitude as the one in Lachowska et al. (2023), and suggests that hours constraints imply large welfare costs for workers.

Related Literature. This work falls within a prominent, although specialized, literature on hour constraints. The theoretical foundations of hour constraints have been established in seminal work by Rosen (1974), then developed and refined (Abowd and Card, 1987; Dickens and Lundberg, 1993; Kahn and Lang, 2001; Bloemen, 2008). This literature intends to provide a framework in order to understand how hour constraints emerge and affect labor markets. Recent contributions to this literature relate hours constraints to the effects of imperfect competition on hours worked

(Manning, 2003; Germain, 2025). The main reference for this paper is Lachowska et al. (2023), who build on a revealed preference approach to quantify welfare effects of constraints. I contribute to this literature by combining a micro-level measure of hours constraints with administrative panel data to reassess important findings of this literature, including welfare effects.

This research also relates to a literature considering hours worked as a job amenity that influences workers' job choices and satisfaction. Hwang et al. (1998), Lang and Majumdar (2004), Lavetti and Schmutte (2016), Sorkin (2018), Lamadon et al. (2022), and Dube et al. (2022) have examined how hours worked affect workers' utility and job preferences. This paper adds to this body of work by estimating how much workers value their working hours.

Because of its relevance for the public economics literature, the relationship between hour constraints and labor supply responses to shocks has been largely explored. Kahn and Lang (1991) discusses the bias in labor supply elasticities due to the presence of hours constraints. Chetty et al. (2011) assess the implications of hours constraints for quasi-experimental estimation of labor supply elasticities. Labanca and Pozzoli (2022) show the unresponsiveness to tax changes in the context of hours constraints. This paper contributes to this literature by assessing the extent of hours rigidities in the labor market and whether they can be circumvented.

Lastly, this paper makes an important contribution to the measurement of true labor supply, to be distinguished from observed hours worked (Pencavel, 2015). The study of hours constraints complements extensive macroeconomic research (Costa, 2000; Bick et al., 2018, 2022) that directly interprets trends in hours worked as evidence of labor supply changes. Recent research by Jarosch et al. (2025) also belongs to this literature by estimating the implied macroeconomic effects of relaxing constraints. In the same vein, another strand of literature (see Bell and Blanchflower (2021)) has focused on the empirical assessment of underemployment, focusing on different countries and discussing the potential origins of this phenomenon. This paper reinforces the claim that hours constraints are a major feature of labor markets and should be invoked in all discussions related to working time.

2 Theoretical Framework

This section provides a theoretical framework for the study of hours constraints. Most of the framework is directly derived from the Lewis-Rosen model under imperfect competition introduced by Lachowska et al. (2023). The main difference is the introduction of a worker-specific parameter α_i that intervenes in the employer's technology. This addition implies that an employer may have heterogeneous preferences on working hours for different workers, even if they have similar preferences. At the end of the section, I discuss conditions under which constrained workers are able to adjust their hours. This framework serves as an illustration to the empirical work realized in the further sections.

Workers are indexed by $i = 1, \ldots, N$ and have preferences on earnings and hours represented by utility $u_i(.)$, increasing in earnings and decreasing in hours. The (hourly) wage w is defined as the ratio between earnings and hours. For each worker, the optimal number of hours worked h^* is defined by the equality between the marginal rate of substitution (MRS) between earnings and hours and the observed wage:

$$\text{MRS}_{e,h}(e, h^*) = -\frac{\partial u_i(e,h)}{\partial h} \bigg/ \frac{\partial u_i(e,h)}{\partial e} \bigg|_{h=h^*} = w$$

Employers are indexed by $j = 1, \ldots, J$ and have heterogeneous technologies inducing employer-specific revenue functions $R_j(.)$. The revenue function depends on the number of hours worked and on a worker-specific parameter α_i corresponding to the perceived return to an additional hour of work $(\frac{\partial R_j}{\partial \alpha_i} > 0)$. For simplicity, I depart from the original model by not assuming a maximum number of productive hours. The profit function of employer j for a given match with worker i is $\Pi_j(h, \alpha_i, w) = R_j(h, \alpha_i) - wh$.

The matching process between workers and employers is not described in the Lewis-Rosen model. We instead focus on the determination of hours and wages once the match has occurred. Under imperfect competition, firms are able to impose a firm-specific surplus $k_j(\alpha_i)$ that is positive, linear on α_i, and is allowed to vary on worker productivity in both directions. The Nash bargaining problem that generates hours and wages at the equilibrium is given by:

$$\left(w_{ij}^b, h_{ij}^b \right) = \underset{w,h}{\text{argmax}} \; u_i(e, h) \text{ s.t. } \Pi_j(h, \alpha_i, w) = k_j(\alpha_i) \tag{1}$$

The number of hours that solves the optimization problem, h_{ij}^b, is defined by the equality between the MRS and the marginal revenue of hours:

$$\text{MRS}_{e,h}(e, h) = \frac{\partial R_j(h, \alpha_i)}{\partial h} \tag{2}$$

The firm-specific surplus does not intervene in the determination of hours. The number of hours worked in a given firm is generated by the properties of its revenue function R_j and the perceived level of productivity α_i. Since the revenue function depends on the worker-specific productivity, the number of hours worked in a given firm can vary between workers with identical preferences. The marginal revenue of an additional hour of work is increasing in α_i, then $h_{ij}^b < h_{rj}^b$ for two workers i and r with $\alpha_i < \alpha_r$.

The bargained wage w_{ij}^b is then derived as the average revenue per hour marked down by a profit margin that depends on the match-specific surplus $k_j(\alpha_i)$[3]:

$$w_{ij}^b = \frac{R_j(h_{ij}^b, \alpha_i)}{h_{ij}^b} \left[1 - \frac{k_j(\alpha_i)}{R_j(h_{ij}^b, \alpha_i)} \right] \tag{3}$$

Then, the bargained wage varies based on the firm-specific revenue function $R_j(.)$ and the worker-specific parameter α_i. The reaction of the equilibrium wage to a change in α_i can be decomposed into three components representing (i) the change in the revenue function, (ii) the indirect change in labor cost driven by the reaction of bargained hours, and (iii) the change in the match-specific surplus[4]:

$$\frac{\partial w_{ij}^b}{\partial \alpha_i} = \frac{1}{h_{ij}^b} \cdot \left[\frac{\partial R_j(h_{ij}^b, \alpha_i)}{\partial \alpha_i} - \frac{\partial h_{ij}^b}{\partial \alpha_i} w_{ij}^b - \frac{\partial k_j(\alpha_i)}{\partial \alpha_i} \right] \tag{4}$$

Workers are constrained from above at the equilibrium if their MRS is lower than the bargained wage, as they would accept to work one more hour for less than the bargained wage. Hence, a given worker i in firm j is constrained from above if

$$\left. \frac{\partial R_j(h, \alpha_i)}{\partial h} \right|_{h=h_{ij}^b} < \frac{R_j(h_{ij}^b, \alpha_i)}{h_{ij}^b} \left[1 - \frac{k_j(\alpha_i)}{R_j(h_{ij}^b, \alpha_i)} \right]$$

If we use a revenue function of the form $R_j(h, \alpha_i) = h^{\alpha_i} T_j$ as in the original model with T_j representing the firm-specific production technology, the condition for worker i to be constrained

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[3]See Appendix B in Lachowska et al. (2023) for proofs.
[4]See Appendix C.1 for the proof.

from above can be expressed as:

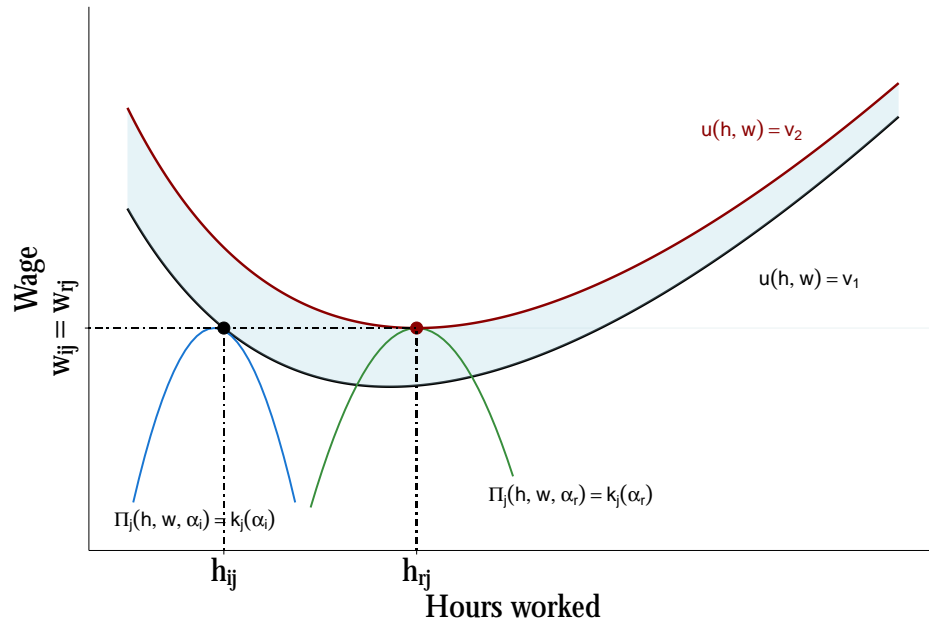$$\alpha < 1 - \frac{k_j(\alpha_i)}{R_j(h_{ij}^b, \alpha_i)}$$

Note that in this framework, workers who are constrained from above generate decreasing returns to work ($\alpha < 1$), as already pointed out by Lachowska et al. (2023). Assuming that employers retain a uniform markdown on all their workers, i.e. $k_j(\alpha_i)/R_j(h_{ij}^b, \alpha_i)$ is constant across α_i, the probability to be constrained from above is decreasing as the worker productivity gets higher. This property still holds, under some regularity conditions, when letting the ratio vary across workers. Hence, workers who end up constrained from above are likely perceived as less productive by their employers.

Decision To Move.   We now examine how workers adjust their hours toward their desired levels. Bargained hours in a given firm can only vary in reaction to a change in the worker productivity α_i. For instance, this may reflect a change towards an occupation that implies a different return to hours. However, constrained workers are more likely to close the gap between actual and desired hours by moving to firms with different production technologies.

Consider two workers i and r with identical preferences $u(h, w)$ working at the same firm j but differing in productivity: $\alpha_i < \alpha_r$. Due to this productivity gap, the workers supply different hours, with worker i constrained from above and worker r operating on their optimal labor supply curve. Worker r therefore attains a higher utility level: $u(h_{rj}, w_{rj}) > u(h_{ij}, w_{ij})$. This creates asymmetric mobility incentives. Wage-hour bundles exist that would raise worker i's utility but not worker r's, generating a larger set of acceptable outside offers for the constrained worker. Figure 1 illustrates this difference: the blue region represents bundles that worker i would accept but worker r would reject, which demonstrates that constrained workers face stronger incentives to move than their unconstrained counterparts with similar preferences.

Consequently, constrained workers can adjust their hours by moving to firms with more efficient production technologies, provided the wage loss from any markdown policies is not too severe. This framework shows that hours constraints arise from the interaction of firm heterogeneity and worker-specific characteristics, and that employer-to-employer transitions to more productive firms represent the most effective mechanism for hours adjustment.

Figure 1: Decision To Move for Constrained and Unconstrained Workers

Note: This figure illustrates the decision to move for two workers with identical preferences but different productivity levels working at firm j. Worker i (constrained from above at hours h_{ij}) operates below their optimal labor supply curve, while worker r (unconstrained at hours h_{rj}) operates on their optimal labor supply curve. $\Pi_j(h, w, \alpha_r) = k_j(\alpha_r)$ and $\Pi_j(h, w, \alpha_r) = k_j(\alpha_r)$ correspond to firm j's iso-profit curves for different levels of productivity and match-specific surplus. The black and red curves represent indifference curves, with worker r attaining higher utility ($v_2 > v_1$). The blue-shaded region shows wage-hour bundles that worker i would accept (above indifference curve v_1) but worker r would reject (below indifference curve v_2).

3 Data

I mobilize for the period between 2003 and 2023 two classic data sources for the study of the labor market in France: the French Labour Force Survey, the *EEC*, and the French matched employer-employee dataset, the *DADS*[5]. Furthermore, both sources are used to build a newly matched dataset, the *EEC × DADS* which combines their information at the individual level. Beyond its purpose for this paper, this unique linkage constitutes an important contribution to the integration of survey and administrative datasets.

3.1 French Labour Force Survey (EEC)

The *Enquête Emploi en Continu* (EEC) is a large-scale nationally representative survey conducted by the French National Institute of Statistics and Economic Studies (*Insee*). Like every other European Labour Force Survey, it complies with the guidelines of the International Labour Organization (ILO) and of Eurostat. Designed to provide a thorough understanding of the labor market dynamics, the EEC collects detailed information on workers' characteristics at a quarterly frequency for a maximum period of 6 quarters. The sample is restricted to non-agricultural salaried workers between 18 and 64 years old. Reported variables include standard demographic and labor market indicators such as age, municipality of residence, occupation, and labor earnings, as well as a broad range of measures capturing worker preferences. Hours worked, which are central to this paper, correspond to the usual number of hours per week[6]. The occupation classification system underwent two revisions during the observation period, in 2008 and 2020. I harmonize occupation codes throughout the entire period using correspondence tables provided by Insee. When the correspondence tables do not provide a perfect 1-to-1 match at the 4-digit level (497 values), I assign observations to the most common occupation code in the new classification. Most importantly, the survey contains specific variables that I use to provide direct measures of hours constraints.

Hours constraints are measured using binary responses to questions (STPLC and STMN) asking workers whether they *"want to work* [more/less] *hours in their job with a corresponding* [increase/decrease] *in earnings"*. Workers who report they would want to work more or less are respectively denoted as constrained *from above* or *from below*, following the terminology of La-chowska et al. (2023). Workers who answer no to both questions are referred to as *unconstrained*.

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[5]As in previous work, e.g. Godechot et al. (2023); Bergeaud et al. (2025), I refer to this data as DADS with a slight abuse of notation, as its official name is *Base Tous Salariés*.

[6]The EEC also includes the number of hours worked during the reference week in which the worker is surveyed. I do not use this variable as it relies too heavily on volatile parameters.

The specification *"with a corresponding income variation"* is designed to elicit workers' optimal hours at their current hourly wage, consistent with traditional labor supply models. The nonresponse rate is less than 1%, making this variable well-suited for analysis. When individuals respond affirmatively to either question, they are subsequently asked *"the number of hours that they would ideally work with a corresponding income variation"*. This follow-up question yields a measure of desired hours for constrained workers, providing an intensive margin component to our constraint measures. In the group of workers constrained from above, I define as *involuntary part-time* workers the individuals who work part-time and report desired hours per week superior or equal to 35, which corresponds to the French reference duration. More than 70% of part-time workers constrained from above are in this case.

These questions appear in all European Labour Force Surveys, and have been frequently used to measure hours constraints in previous research (see e.g. Gaini and Vicard (2012); Beckmannschagen and Schröder (2022); Asai (2024) or more recently Jarosch et al. (2025)). However, the reliability of the answers can be questioned as common survey biases apply here (see Stantcheva (2023)). Understanding how workers perceive questions regarding the distance to their ideal hours, and whether their answers are truly indicative of constraints, is a priori challenging. Validity concerns are addressed to a certain extent by exploiting other survey information from the EEC. For instance, 95% of workers who report constraints from above report their availability to work more, the share being slightly higher for part-time workers. This provides evidence that constraints do not reflect mere preferences that are not in regard to real-life constraints (e.g. child caring). These workers have internalized their work environment and are ready to work more. Appendix B2 presents additional evidence on work motivations, persistence of preferences and worker mobility over the 6 quarters of observation to discuss the interpretation and reliability of this variable. It also includes descriptive statistics regarding the distribution of desired hours in the sample.

Importantly, I use a version of the French Labour Force Survey that provides access to the establishment identifier (the *SIRET*) for each worker's place of employment, as coded by Insee based on information from the worker's payslip. This feature, which to my knowledge is unique to the French version of the survey, is crucial to this study. The remainder of the paper considers only individuals for whom the *SIRET* information is available—82% of the original sample. This dataset enables the study of hours constraints observed at the worker level while accounting for firm-specific effects, a contribution that lies at the heart of this paper.

3.2 French Matched Employer-Employee Dataset (DADS)

The second source of data is the French matched employer-employee dataset *Base Tous Salariés* based on social security records (the *Déclarations Annuelles de Données Sociales / Déclaration Sociale Nominative*) and hereafter called *DADS*, notoriously used in Abowd et al. (1999). The dataset is constructed by Insee, based on administrative employer reports (mandatory for each employee subject to French payroll taxes) containing information on characteristics of the worker. In particular, it includes their income, paid hours worked, and length of employment spell. I use the *Fichiers Postes* version of the *Base Tous Salariés*, an exhaustive version that covers all jobs in the entire salaried workforce in each calendar year. The chaining procedure described by Godechot et al. (2023) is then used to build a quasi-exhaustive DADS panel dataset over the period between 2003 and 2023, which enables the observation of employer-to-employer transitions for almost the entire workforce.

Using employer-reported paid hours worked as a measure of actual hours worked raises methodological concerns. Paid hours, as reported in the DADS, include all remunerated periods, i.e. not only regular working weeks but also paid leave. Hence, these hours tend to reflect contract hours and are uncertain to capture small adjustments. Appendix B3 assesses the quality of hours worked data by reproducing the approach of Lachowska et al. (2022) on Washington state administrative data, augmented with features specific to French labor regulations and data[7]. The implemented tests suggest that the quality of the data is comparable to the data used in Lachowska et al. (2022). As expected, paid hours tend to be quite concentrated around the reference duration (about 30% of the population works 35 hours per week) but there remains substantial variation likely driven by part-time work and overtime hours.

A particular feature of French working time regulations requires special consideration. *Forfait jours* contracts, covering approximately 15% of the workforce in 2019, measure working time in annual days rather than weekly hours. Under this arrangement, employers are not required to monitor or report actual hours worked in DADS records[8]. Insee addresses this data gap by imputing standardized annual hours (typically 1,820 or 2,200 hours depending on the year) of these workers, identifiable through the UNITMESUREREF variable since 2017. Given that these

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[7]In particular, the linkage of EEC and DADS datasets allows me to compare employer-reported and employee-reported hours for the same worker. Such comparisons have already appeared in previous research by Frazis and Stewart (2010). This work yet stands out as I rely on a much larger sample and on an administrative source of information on the employer's side.

[8]Breda et al. (2025) provides more background on this type of contracts and addresses the implications of workers' misperceptions about them on working conditions.

imputed values do not reflect actual working time and would introduce systematic measurement error into the analysis, workers in occupations with a large share of *forfait jours* contracts are excluded from the sample throughout most of the paper, with exclusions explicitly noted.

3.3   EEC × DADS Sample

Finally, the EEC and DADS datasets are linked together to build a unique new data set. Given the quasi-exhaustive nature of the DADS data on employment spells, most individuals surveyed in the EEC should appear in the DADS. In addition, workers should be identifiable based on information on age, sex, occupation, part-time/full-time work, birth department, birth month (only between 2009 and 2012), residence municipality, and crucially, establishment ID, which is supposedly consistent across sources. This information is thus mobilized to build a correspondence table between individual identifiers of both datasets. The procedure follows a "1-to-1"[9] matching approach on common variables, i.e. workers surveyed in the EEC are identified in the administrative records based on precise identical information across sources. This linkage is made possible by the presence in the EEC of the worker's establishment's ID (the *SIRET*). Importantly, the method used here relies on fuzzy matching, and thus can theoretically lead to errors in ID linkage. However, I reckon that the high precision of variables used and the conservative decision to remove all "1-to-many"[9] matches ensure a reliable linked dataset. The linkage is performed for every year between 2003 and 2023, keeping all quarterly information from the EEC and yearly information on all employment spells from the DADS. Appendix B3 details the entire matching procedure.

The operation yields a sample of 435,472 perfectly matched individuals between 2003 and 2023, a coverage of 67% of the EEC sample of employees[10] on this period. Cases where individuals cannot be matched across sources occur for three main reasons: (a) the establishment's ID is missing or incorrectly reported by the worker, (b) individuals are dropped during the cleaning process of the DADS as their information on hours or earnings is missing, (c) multiple workers cannot be distinguished based on the matching variables. The quarterly nature of the EEC and the linkage of all DADS employment spells (including secondary jobs) over the period imply multiple observations per worker and year, hence generating a sample of 1,695,359 observations. This sample, hereafter denoted as the EEC-DADS sample, shows reasonably representative as described

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[9]I refer to a "1-to-1" match in this context to describe a situation where exactly one worker in the DADS dataset corresponds to exactly one worker in the EEC dataset based on identical values for the specified matching variables. Likewise, a "1-to-many" match depicts a situation where multiple workers in the DADS dataset corresponds to a unique worker in the EEC.

[10]After removing observations with missing number of hours worked or missing establishment's ID.

by summary statistics in Table A1. The most striking disparity with respect to the original EEC sample is the sizable under-representation of constrained part-time workers (representing 26% of part-time workers in the EEC-DADS sample against 34% in the original). This likely occurs because this population tends to hold more precarious positions with lower compliance on administrative duties, thus affecting the reliability of their information in both sources. As a result, the hours constraints that affect the part-time population in the EEC-DADS sample should reflect more stable and structural constraints than those in the original EEC sample. This is consistent with validity checks in the data: part-time workers who wish to increase their hours hold a permanent job more frequently (72% against 60% in the original sample) and have more experience in their current firm (76% have more than 1 year against 70% in the original sample).

Then, 92% of the workers in the EEC-DADS sample are connected, using their yearly DADS identifier, to the previously chained DADS panel between 2003 and 2023. This dataset is denoted as the *EEC-DADS Panel*. As discussed in Godechot et al. (2023), the DADS panel is not fully exhaustive, which explains why some workers of the EEC-DADS sample cannot be recovered. The EEC-DADS Panel combines for each individual EEC-based information over 6 quarters of observation, hereafter the *EEC period*, and DADS-based information over the period of appearance in the panel. In other words, it contains information on individual preferences in terms of hours over a short period of time and on their employment history over a long period. The particular structure of this dataset is illustrated in Figure A1. The EEC-DADS panel gathers information on 399,553 individuals appearing 10 years on average in the panel, sometimes with multiple spells of employment over one year, resulting in a total of 9,734,018 observations.

This unique dataset paves the way for new empirical work on the topic of hours constraints by combining a self-reported measure from the Labour Force Survey with the panel dimension and reliability of administrative employer-employee datasets. Beyond this study, this dataset has potential applications across a wide range of research purposes, as the Labour Force Survey includes extensive information on various topics.

4 Sorting of Constrained Workers

This section provides new empirical evidence on the topic of hours constraints by exploiting an individual survey-based measure linked with employer information. Section 4.1 presents the main characteristics of workers who report being constrained in their hours using the entire EEC sample. Section 4.2 examines the role of firm sorting in shaping hours constraints by studying the heterogeneity of firm policies on hours through an AKM decomposition. Section 4.3 quantifies the gap in hours between constrained and other workers captured by each type of sorting and tackles the remaining heterogeneity inside the workplace.

4.1 Worker Preferences

This section examines the characteristics of workers who report ideal hours above their current level. The goal is to understand what types of workers express these preferences and to ultimately inform the main results of the paper.

As presented in Section 3, three groups of workers are distinguished based on their answer to questions relevant to hours preferences in the Labour Force Survey: workers *constrained from above* who report that they ideally want to work more hours at their given wage rate, workers *constrained from below* who report that they ideally want to work less hours at their given wage rate and *unconstrained* workers who report no will to work different hours at their given wage rate. The defined groups respectively represent 19%, 2.5% and 78% of the Labour Force Survey sample between 2003 and 2023. This indicates that nearly one out of five salaried workers is constrained from above, while the share of workers constrained from below is minimal[11]. For this reason, the term *constrained* is used in all following sections of the paper to refer to the constrained-from-above situation.

The French working time regulation splits employees in two groups based on their working hours. Workers who are hired in a contract with strictly less than 35 hours per week (the reference duration in France) are part-time workers, while others are full-time workers. The distinction between these two types of workers is done throughout the paper. The EEC sample consists of 112,523 part-time workers and 512,944 full-time workers. The sample has been restricted to salaried workers with non-missing hours worked and an hourly wage between 0.8 and 1000 times

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[11]This stands in sharp contrast with the prevalence of overwork in the German case, as documented by Jarosch et al. (2025). As mentioned in Cohen et al. (2025), the distributions of desired hours are similar across countries but actual hours are higher in Germany, hence the difference in the direction of constraints.

the hourly minimum wage. Part-time workers are largely over-represented in the constrained-from-above population: 34% of part-time workers report that they would ideally increase their hours, as opposed to 17% among full-time ones (see Table A1). About 70% of these constrained part-time workers are *involuntary part-time* workers, i.e. they would ideally work as full-time employees, as derived from their desired hours[12].
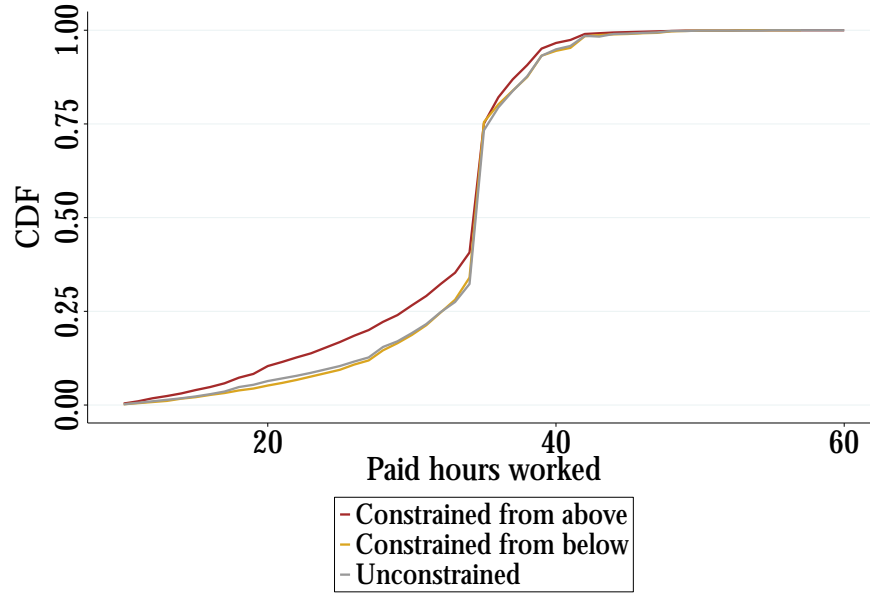
Figure 2 displays the cumulative distribution functions of paid hours worked by groups of workers' preferences. The sample used is the matched EEC-DADS sample in order to use hours from the administrative data rather than reported usual hours worked. The figure reveals a clear pattern: workers who prefer to increase their hours (red curve) work systematically fewer hours than those who are satisfied with their current hours (gray curve) or prefer to decrease them (yellow curve). The distribution of hours for constrained-from-above workers is strongly left-shifted as part-time workers are overrepresented in this group. The three curves converge closely around standard full-time hours, with constrained-from-above workers working only about 0.1 hour per week less than other groups. It means that constrained full-time workers do not significantly differ from other full-time workers in terms of hours worked. Rather, they stand out by their preferences for longer hours.

Figures 3a and 3b illustrate how the shares of constrained workers vary in the (hourly) wage distribution, separately for part-time and full-time workers. Both figures show that preferences for a higher number of hours are regressive in wages, in particular in the part-time case. A simple interpretation of the pattern is that some workers aim to increase their earnings through hours worked to compensate for low wages (consistently with Figure B1b), i.e. the "income effect" dominates. Conversely, the probability to be constrained from below is positively correlated with wages, although it remains marginal even at the top of the wage distribution.

The relation between worker preferences in hours and wages well summarizes the profile of each group and Table A3 presents further details about their composition. Determinants of being constrained from above include being young, low-skilled, born outside of France, employed in a private sector firm, employed in a small firm and in a non-permanent contract. As noted earlier, the constrained-from-above group has many more part-time workers, which lowers their average hours. The subgroup of involuntary part-time workers is very different from the rest of constrained workers, as women, mostly working in low-skill tertiary jobs, represent a large majority of this group.
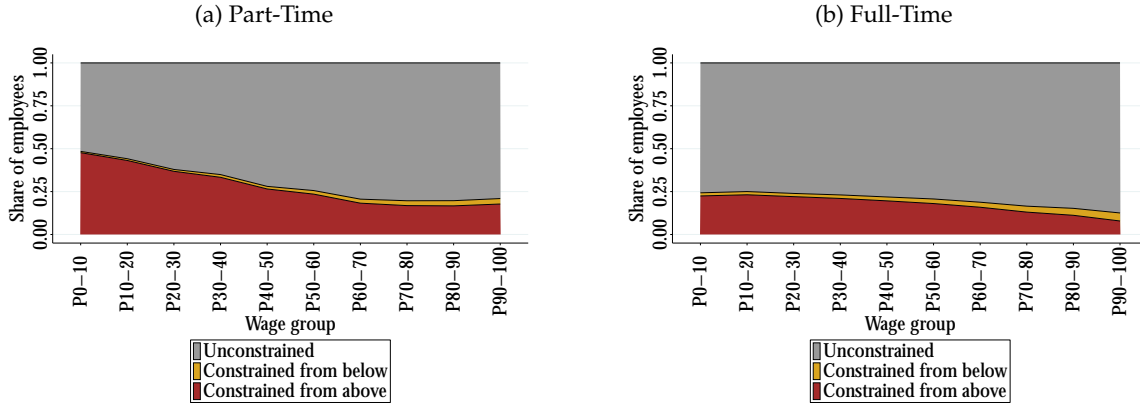
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[12]This corresponds to the PTWFT category in the *underemployment* literature (see e.g. Bell and Blanchflower (2021)).

Figure 2: Hours Worked by Group of Workers' Preferences

Note: The figure shows the cumulative distribution functions of paid hours worked by group of workers' preferences based on the EEC-DADS sample. Three groups are considered based on their answers to the following questions in the surveys: *"do you ideally want to work* [more/less] *hours in your job with a corresponding income variation?"*. "constrained from above" workers report that they ideally want to work more hours ; "constrained from below" workers report that they ideally want to work less hours ; "unconstrained" workers answer no to both questions. Hours worked are paid hours from the DADS recomputed as full-year equivalent.

Figure 3: Workers' Preferences in Hours in the Wage Distribution

(a) Part-Time   (b) Full-Time

Note: The figures show the distributions of workers' preferences based on Labour Force Surveys pooled between 2003 and 2023. Three groups are considered based on their answers to the following questions in the surveys: *"do you ideally want to work* [more/less] *hours in your job with a corresponding income variation?"*. "constrained from above" workers report that they ideally want to work more hours ; "constrained from below" workers report that they ideally want to work less hours ; "unconstrained" workers answer no to both questions. Wage deciles are defined within year and employment status (part-time/full-time).

Figure A2 shows the distribution of constrained workers, split by working time status, across industries, ranked by the share of part-time constrained workers. Few industries gather the ma-

jority of constrained part-time workers. Some of them are notorious for their high reliance on part-time employment, e.g. "Social Care" or "Food and Accommodation", but it is not always the case. Industries from the public sector are particularly high ranked, with most of the constrained workers in these, including in "Education", being maintenance workers. The distribution is relatively similar for full-time constrained workers, although other industries stand out. For instance, the sectors of "Construction", "Transport" and "Consulting" each gather more than 5% of full-time constrained workers. Figures A3a and A3b provide an even more striking picture for occupations. Part-time workers who want more hours are heavily concentrated in low-wage jobs, e.g. five occupation groups (personal care workers, cleaners in the public and private sector, sales employees, and cooks) account for half of constrained part-time workers, while representing only 30% of all part-time workers (including voluntary ones). On the other hand, full-time workers are relatively distributed evenly across occupations with no clear concentration in low-wage jobs.

This section documents that workers who want to increase their hours work on average less hours than other workers. The gap is yet almost entirely related to the higher proportion of part-time workers, as average hours of full-time workers are very similar across constrained and unconstrained workers. For full-time workers, the desire to work more hours mostly stems from differences in preferences rather than in actual hours worked. On the other hand, most constrained part-time workers report wanting a full-time job, i.e. the preferred working time status of the majority of workers, but fail to access these jobs. Next section studies to what extent their hours constraints are driven by firm-specific features.

4.2 Firm Sorting

This section studies the role of firm sorting in the phenomenon of hours constraints. I take advantage of the presence of establishments' IDs in the French Labour Force Survey to examine the distribution of constrained workers across firms. This approach complements recent work by Labanca and Pozzoli (2023) on the role of firms in hours constraints using direct survey-based evidence of these constraints. This measure also enables to connect worker hour preferences with employer hour policies, a relation at the heart of Lachowska et al. (2023)'s work, by which this section is largely inspired. The section further provides evidence on the interaction between firm effects and occupational effects, i.e. the extent to which firm heterogeneity explains hour variation within occupations.

AKM Estimation. As in Babet and Chabaud (2024), I use a chained DADS panel between 2005 and 2019, quasi-exhaustive of the French salaried workforce, and apply several restrictions to the sample[13]. Hours worked are annualized paid hours, and wages correspond to real net hourly wages. The sample is also restricted to the largest weakly connected set of firms, as is common in this literature (Card et al., 2013). The estimation sample contains 29,824,763 workers and 1,318,726 firms. The following model is fitted:

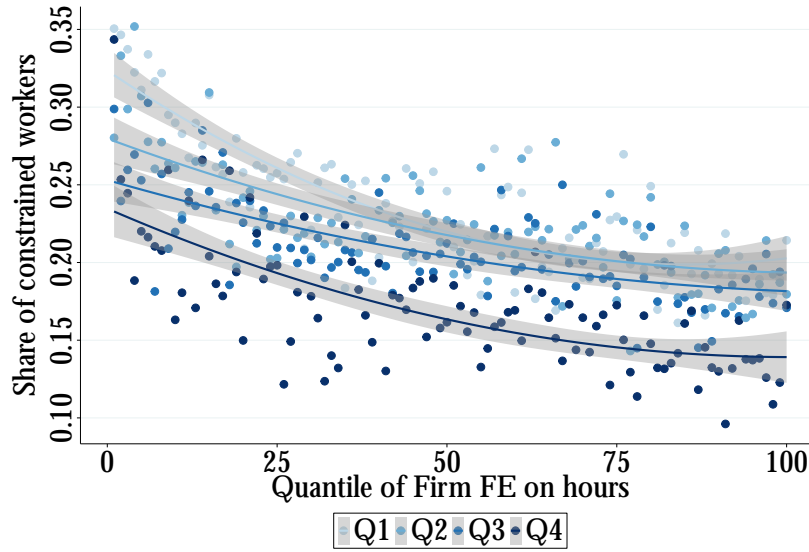$$y_{it} = \phi_i + \psi_{j(i,t)} + X_{it}\beta + u_{it}$$

with y_{it} the logarithm of the outcome (either hours or wages) of worker i in year t. ϕ_i is the fixed effect of worker i, and $\psi_{j(i,t)}$ is the fixed effect of firm $j(i,t)$, the employer of worker i during year t. ψ_j is therefore a measure of firm j's premium in the corresponding outcome, i.e. the component of hours or wages that is due to the general policy of the firm. Time-varying covariates X_{it} are limited to fixed effects for years and age as a cubic polynomial. u_{it} is the idiosyncratic error term. This model can be used to decompose the variance in hours and wages into components associated with worker and firm heterogeneity and sorting, as done in Babet and Chabaud (2024) with the same data. The goal here is rather to use the estimated employer effects for their interpretative value. Figures A4a and A4b show an event study check popularized by Card et al. (2013) to assess the plausibility of exogenous mobility in the analysis sample, respectively for hours and wages. In both cases, evidence suggests that the specification with fixed worker and employer effects rationalizes well the evolution of outcomes across moves in the data.

Job Ladder. Employer effects are split into percentiles and each combination of hour-effect percentile and wage-effect quartile is associated with the share of workers within the cell who report constraints from above. Thus, each combination characterizes groups of firms with similar policies in hours and wages. Figure 4 shows a distinctive pattern of worker preferences related to firm policies. The share of constrained workers is at its highest level in firms with low-hour and low-wage (Q1) policies, and decreases as the group of firms is associated with higher levels of hours or wages. This result is consistent with the idea of a job ladder across firms, previously introduced

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[13]Workers aged between 18 and 64, in ordinary jobs of more than 120 hours and 60 days, with hourly wage greater than 0.8 minimum wage and smaller than 1,000 minimum wages. I also keep only one observation per person-year so I take the annual dominant employer of the worker (defined as the employer from which the worker earns the most during the year). Occupations with more than 20% of forfait jours workers in the EEC between 2013 and 2023 are excluded from the sample.

in Lachowska et al. (2023) as a mechanism of hours constraints, i.e. a hierarchical ranking of employers based on the desirability of their jobs. In other words, most workers want to work for the same firms, those with high employer effects, but limited availability of those jobs implies that some of them end up as constrained in lower quality jobs. By combining individual-level survey information on constraints with firm effects on hours, this figure provides prominent empirical evidence for this mechanism in the case of hours constraints.

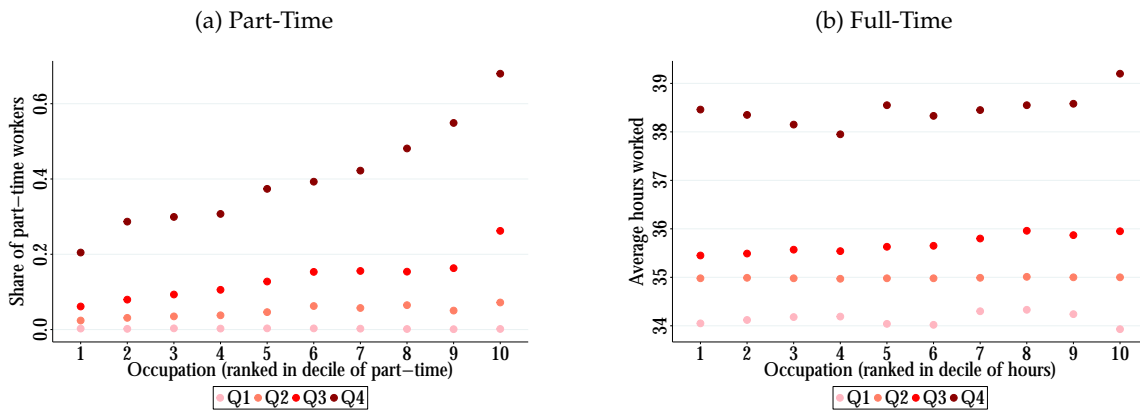Figure 4: Hours Constraints and Firm Policies

Note: This figure represents the relationship between hours constraints and AKM firm effects on hours and wages. The x-axis represents the percentile of firm fixed effect on hours, while the y-axis shows the share of workers constrained in their hours. The four groups (Q1-Q4) represent different firm wage-effect quartiles, with darker points indicating higher wage quartiles. All firm effects are estimated through an AKM decomposition. The data used is a panel based on chained DADS yearly files between 2003 and 2023. See the text for details. Hours worked are paid hours recomputed as full-year equivalent. Shaded areas correspond to 95% heteroskedasticity-robust confidence intervals.

Firm Heterogeneity in Occupation Effects. Next, I explore whether firm sorting relies on firm heterogeneity within a given occupation, by examining the interaction between firm and occupation effects on hours. Figures 5a and 5b plot average hours by groups of firms and occupations, respectively for part-time and full-time workers. where firms are divided into quartiles based on their share of part-time workers (a) or average hours worked (b), and occupations are grouped into deciles using the same respective measures. In the part-time case, the share of part-time workers is used because hours constraints mostly reflect the inability to work full-time. Then, limitations that may arise from firm or occupation effects are more related to the proportion of full-time, thus part-time, jobs than to the average number of hours. Each point in the figures respectively

represents the share of part-time work or average hours worked for a specific firm-occupation group. For full-time workers, the profiles across occupation deciles are relatively flat within each firm quartile, which reflects limited variation in hours across occupations within a given type of firm. Conversely, for each decile of occupation effects, the vertical gap in hours between firms of different quartile is large. This means that the variation in hours in a given occupation can be substantial and that firm effects account for most of the variation in hours across full-time workers. For part-time workers, profiles depict an upward slope in firms that are intensive in part-time work. This indicates that firms do not equally rely on part-time work for different occupations. As for full-time workers, a large variation in shares of part-time work exists within decile of occupations, which suggests that firms differ in their use of part-time work in a given occupation. Hence, involuntary part-time work is likely driven by a combination of firm and occupational effects.

Figure 5: Firm Heterogeneity in Occupation Effects

(a) Part-Time

(b) Full-Time

Note: This figure represents the average hours worked by group of firm and occupation. Data is based on DADS yearly datasets pooled between 2009 and 2023. Hours worked are paid hours recomputed as full-year equivalent. Occupations correspond to the 3-digit level in the PCS classification (110 values). Deciles of hours worked are derived from average (paid) hours worked per week computed at the occupation level. For example, the first group on the x-axis corresponds to the 10% of workers who work in occupations with the lowest average hours. Firms are ranked by average paid hours worked of their employees and divided into quartiles.

4.3   Decomposing the Variation in Hours near Constrained Workers

This section synthesizes previous sections by quantifying the role of each component in the gap in hours between workers who I identify as constrained and the rest of employees. As explained in Section 4.1, the gap is primarily driven by the over-representation of part-time workers in the sample of constrained workers. In this section only, I restrict the focus to involuntary part-time workers and I discuss the role of structural barriers such as occupation and firms to explain their

inability to get a full-time job. The hypothesis that is evaluated here is that involuntary part-time workers are employed in parts of the labor market where there are very few full-time jobs. The ultimate question will be: do involuntary part-time workers have colleagues in the same occupation with a full-time contract?

To address this question, I consider all workers in the DADS yearly datasets who work in the same firm and occupation as a worker identified as an involuntary part-time worker in the EEC. Given the exhaustive nature of this data, this definition should gather all simultaneous coworkers of the involuntary part-time workers from my sample. Note that the methodology does not capture coworkers' preferences but instead provides a comprehensive view of the hours distribution surrounding constrained workers. The goal is to understand why some workers work more hours, or have a full-time job, while similar workers are unable to do so. Occupations are defined at the 3-digit level (110 values), which ensures a comparison to similar coworkers. Following Babet and Chabaud (2024), I apply similar filters the data to ensure the relative stability of coworkers in their job: workers are aged between 18 and 64, have a stable working contract (*CDD* or *CDI*) lasting at least 60 days, with annual hours above 120, and hourly wage between 0.8 and 1,000 times the minimum wage.

The sample is also restricted to years between 2009 and 2019 for two reasons. First, the occupation variable (PCS) in the DADS is only consistently coded at the 3-digit level from 2009 onward and the classification changes in 2020. For this exercise only, I consider the strategy too sensitive to potential measurement errors related to the correspondence table between classification to include years after 2020. Second, in the second part of the section, I compare the characteristics of involuntary part-time workers and full-time workers in the same firm and occupation. One of the characteristics included is the worker's tenure in their current firm, recovered using the DADS Panel. Since the panel extends back to 2003, I restrict the data to 2009 and winsorize tenure values above five years. After restrictions, the sample is composed of 897,362 observations, including 4,636 involuntary part-time workers.

Table 1 reports the difference in hours worked between involuntary part-time workers and other workers using varying sets of controls and fixed effects. The original gap in hours in this sample is 16.9%, to be compared to 22.1% in the whole sample[14]. After controlling for simple demographics (age, gender and county of residence) and year fixed effects, the gap decreases to

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[14]Restricting to firm $\times$ occupation combinations with at least one involuntary part-time worker implies a focus on jobs where part-time work is common, hence the decrease in the gap.

14%. The successive introductions of an occupation and a workplace fixed effect reduce the gap respectively to 12.6% and 10.1%. The magnitude of the decrease can be interpreted as the role of sorting associated with each component. Then, the particular employment structures of occupation and firms of involuntary part-time workers each account for between 10 and 15% of the difference in hours. This approach thus validates previous descriptive statistics on the concentration of constrained workers in short-hour occupation and firms. The last specification includes an occupation × workplace fixed effect to measure the difference in hours to close coworkers. The estimate barely changes as it is rare to find an involuntary part-time worker in two different occupations within the same workplace. At this very local level, involuntary part-time workers remain on the lower part of the distribution of hours, as quantified by the final 10% gap. In the sample, 79% of occupation × workplace combinations have at least one full-time worker and the average share of coworkers with a full-time contract is 65%, which means that involuntary part-time workers are mostly employed in jobs with a majority of full-time workers. This result can be seen as surprising, as one could expect a large coordination in hours within workplaces, motivated by production rigidities and the practice of collective hours schedules (Kahn and Lang, 2001).

Table 1: Involuntary Part-Time Workers in the Distribution of Hours

Dependent Variables:	Log Hours Worked				
	(1)	(2)	(3)	(4)	(5)
Involuntary Part-Time	-0.169***	-0.141***	-0.126***	-0.101***	-0.100***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Controls and Fixed-effects					
Year	X	X	X	X	X
Demographics		X	X	X	X
Occupation			X	X	
Workplace				X	
Occupation × Workplace					X
Baseline	32.4	32.4	32.4	32.4	32.4
Observations	897,362	897,362	897,362	897,362	897,362
Adj. R^2	0.01	0.10	0.22	0.29	0.29

*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05.*

Note: This table presents OLS estimates of the difference in hours worked between workers labeled as involuntary part-time workers and others. The data used is the EEC-DADS sample between 2003 and 2023 (see Section 3.3 for more details). The sample is restricted to occupation × workplace combinations with at least one involuntary part-time worker. The dependent variable is log paid hours worked recomputed as full-year equivalent from the DADS. Demographics include age, gender, and county of residence. Occupations correspond to the 3-digit level in the PCS classification (110 values). Occupations with more than 20% of forfait jours workers in the EEC between 2013 and 2023 are excluded from the sample. Standard errors are heteroskedasticity-robust and reported in parentheses.

I investigate mechanisms at work behind the local variation in hours by comparing the characteristics of involuntary part-time workers and their colleagues with a full-time contract. The DADS data includes information on gender, age, type of contract (permanent or non-permanent), native or foreigner status (derived from the birth department variable), distance to workplace (based on residence and workplace municipalities[15]), and tenure in the firm (obtained using the DADS Panel). Age is split in 5 categories to account for non-linearities. As explained above, the tenure variable is winsorized at 5 years.

Table 2 reports the difference in characteristics between both types of workers. For each outcome, the coefficient of interest is estimated in a separate regression controlling for all other outcomes. Involuntary part-time workers differ from their full-time workers in multiple dimensions. Age comes out as a significant driver as involuntary part-time workers have a higher probability to be less than 35. This result should be interpreted cautiously given the over-representation of

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[15]Distances between municipalities are calculated using the Haversine formula, which computes the great-circle distance between two points on a sphere given their latitude and longitude coordinates.

older workers in the EEC-DADS sample (see Table A1). Gender plays a more reliable role: being an involuntary part-time worker, as opposed to a full-time worker, is associated with a 11.7 pp increase in the probability to be a woman. Tenure shows a small negative correlation with hours constraints, which is consistent with the idea that workers are more likely to land a full-time contract after a few years in the same firm. Finally, permanent contracts are slightly positively correlated with involuntary part-time work.

The study of the variation in hours around involuntary part-time workers concludes this section on the sorting of constrained workers. One result of particular interest is the non-negligible dispersion in hours worked, here characterized by the presence of full-time contracts, even at a high proximity to constrained workers. This finding suggests that the determination of hours does not solely depend on firm-level or occupation-level features but may also rely on particular characteristics of the worker. Using survey data on hours preferences, I also provide new empirical support for the existence of firm idiosyncratic preferences over hours, which may generate hours constraints for their employees.

Table 2: Within-Firm Determinants of Hours Constraints

Dependent Variable:	Age					Female	Tenure	Foreigner	Distance	Permanent
	15-24	25-34	35-44	45-54	55+					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Involuntary Part-Time	0.020***	0.016*	0.010	-0.010	-0.033***	0.117***	-0.054**	0.005	-1.083	0.009*
	(0.005)	(0.007)	(0.007)	(0.006)	(0.004)	(0.006)	(0.019)	(0.004)	(0.781)	(0.004)
Observations	567,202	567,202	567,202	567,202	567,202	567,202	567,202	567,202	567,202	567,202
Clusters	3,678	3,678	3,678	3,678	3,678	3,678	3,678	3,678	3,678	3,678
Adj. R^2	0.23	0.11	0.07	0.09	0.10	0.32	0.39	0.17	0.34	0.53
Controls and Fixed Effects										
Year	X	X	X	X	X	X	X	X	X	X
Occupation × Workplace	X	X	X	X	X	X	X	X	X	X
Age (Polynomial)						X	X	X	X	X
Female	X	X	X	X	X		X	X	X	X
Tenure	X	X	X	X	X	X		X	X	X
Foreigner	X	X	X	X	X	X	X		X	X
Distance	X	X	X	X	X	X	X	X		X
Permanent	X	X	X	X	X					

*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05.*

Note: This table presents differences in individual characteristics between involuntary part-time workers and their full-time coworkers. The data used is the EEC-DADS sample between 2003 and 2023 (see Section 3.3 for more details). The sample is restricted to occupation × workplace combinations with at least one involuntary part-time worker. The sample of coworkers is restricted to full-time employees. Occupations correspond to the 3-digit level in the PCS classification (110 values). Occupations eligible to forfait jours contracts are removed from the sample. Age is split in 5 categories to account for non-linearities. Tenure corresponds to the number of years employed in current firm and is winsorized at 5 years due to data limitations. Foreigner is a dummy variable equal to 1 if the individual is born abroad. Distance corresponds to the distance to commute (in kilometers). Permanent is a dummy variable equal to 1 if the individual holds a permanent contract (*CDI*). Standard errors are clustered at the year × workplace × occupation level and reported in parentheses.

5 Labor Market Transitions of Constrained Workers

This section provides first evidence on the evolution of constrained workers in the labor market. The depiction of constraints as mostly driven by occupation and firm effects suggests that workers would have to switch firms to align with their hour preferences. A central analytical focus is to understand to what extent constrained workers can improve their situation through mobility. Section 5.1 studies the relation of hours constraints to worker mobility and presents descriptive evidence on the evolution of hours and earnings. Section 5.2 introduces an event-study framework to estimate differential changes in hours and earnings experienced by constrained workers. Section 5.3 explores the types of mobility by which constrained workers adjust their hours. Section 5.4 discusses the ability for different workers to reach their desired hours. Section 5.5 provides robustness checks to the main estimates.

The entire dynamic analysis relies on the EEC-DADS Panel introduced in Section 3.3 and represented in Figure A1. Similar restrictions to those used by Babet and Chabaud (2024) are applied to the sample[16] and their definition of voluntary moves is used for robustness checks. Additionally, the period of activity is limited to the continuous sequence of years around the EEC period and to individuals who appear both before and after it. After restrictions, the sample is composed of 157,716 workers. 17.5% report wanting to work more hours in the last quarter of their EEC period. This measure of hours constraints is used in the rest of the section and the year of the last EEC quarter serves as the reference year ($t = 0$). Workers appear on average 13.5 years in the panel (the median is 14). In short, the EEC-DADS Panel maintains the same structure as the DADS Panel, supplemented with additional information from the last year of EEC survey administration.

5.1 Worker Mobility

First, the focus is on the relation of hours constraints to mobility. In this first part of the section, worker mobility is measured by a dummy variable equal to 1 if the individual switches employers at least once between years 1 and 3 after the EEC period. The reference EEC employer is adjusted to the last employer reported in the EEC, thus counting any subsequent employer change in year $t = 0$ as a transition in $t = 1$. The three-year observation window is motivated by the persistence

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[16]Workers aged between 18 and 64, stable working contract (*CDD* or *CDI*), annual hours above 120, hourly wage between 0.8 and 1,000 times the minimum wage, and focus on primary employment (defined as the spell that induces highest earnings).

of hours preferences over a short period of time after the EEC[17]. For this part only, the sample is also restricted to employers with at least 2 workers in the sample during their EEC period to allow for the inclusion of an EEC employer fixed effect. The sample used covers 94,503 workers employed in 19,251 firms during their EEC period.

Evidence demonstrates that constrained workers exhibit greater mobility, even in similar employment contexts. Table 3 indicates that constrained workers have a 3.7 pp higher probability of changing employers compared to unconstrained workers over the 3-year span. The coefficient is much higher for part-time ($\beta = 0.102^{***}$) than full-time workers ($\beta = 0.028^{***}$). The magnitude of the coefficient is cut by two when demographic and occupational controls are introduced, but it remains strongly significant. The estimate drops to a 1.2 pp, 7% of the baseline, higher probability of changing firms but remains significant after the inclusion of employer fixed effects. This result means that on average, conditional on a similar employment context during their survey period, constrained workers tend to switch employers more.

Table 3: Hours Constraints and Worker Mobility

Dependent Variables:	Move in Years 1-3			
	(1)	(2)	(3)	(4)
Constrained	0.037***	0.012***	0.018***	0.012**
	(0.003)	(0.003)	(0.003)	(0.004)
Controls and Fixed-effects				
EEC Year	X	X	X	X
Part-/Full-Time (EEC Period)	X	X	X	X
Demographics (EEC Period)		X	X	X
Occupation (EEC Period)			X	X
Employer (EEC Period)				X
Baseline	0.16	0.16	0.16	0.16
Share of Constrained	0.17	0.17	0.17	0.17
Observations	94,503	94,503	94,343	94,343
Adj. R^2	0.01	0.04	0.04	0.36

*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05.*
Note: This table presents estimates of the relationship between hours constraints and job mobility. The data used is the EEC-DADS Panel (see Section 3.3 for details). The sample is restricted to firms with at least 2 workers. The dependent variable is a dummy variable equal to 1 if the individual switches employers between 1 and 3 years after the EEC period. An individual is constrained (from above) if he or she answers yes to the question: *"do you ideally want to work more hours in your job with a corresponding income variation?"* in the Labour Force Survey. Demographics include age, gender and county of residence. Occupations correspond to the 3-digit level in the PCS classification (110 values). Standard errors are heteroskedasticity-robust and reported in parentheses.

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[17]In Appendix B2, I discuss the persistence of hours preferences during the EEC period and find non-negligible instability as only 63% of workers who are constrained in their last EEC quarter are also constrained in their first one. This potential threat is addressed in Section 5.5 by using a more restrictive definition of stable constrained workers. Also note that restricting the window to 2 years after the EEC period barely changes the estimates.

Do constrained workers who switch employers increase their hours? Figure 6 illustrates the trajectories of weekly paid hours worked for four distinct groups: constrained workers and unconstrained workers who switch employers at least once between periods 1 and 3 (respectively *constrained-movers* and *unconstrained-movers*), and their equivalent who remain with the same employer (*constrained-stayers* and *unconstrained-stayers*)[18].

Constrained workers who switch employers experience a large increase in their working hours through mobility. Their upward trajectory contrasts with constrained workers who stay at their original employer, whose hours remain relatively flat and mostly increase through occupational mobility. Unconstrained workers work more hours regardless of whether they change jobs or not and maintain an overall stable level across the observation window. The gap in levels between both groups of constrained workers is mostly due to the higher proportion of part-time workers in the sample of movers.

Figure 6 supports the argument that hours constraints drive job mobility, as constrained workers who switch firms appear to increase their hours towards their desired level, while those who remain in the same firm show more stability. This stability suggests that workers classified as constrained have little influence over hours within their current firm, and must switch firms to adjust them. Figure A5 shows that hour trajectories translate to earnings in an attenuated way, with constrained-movers experiencing a modest increase in earnings immediately after the EEC period.
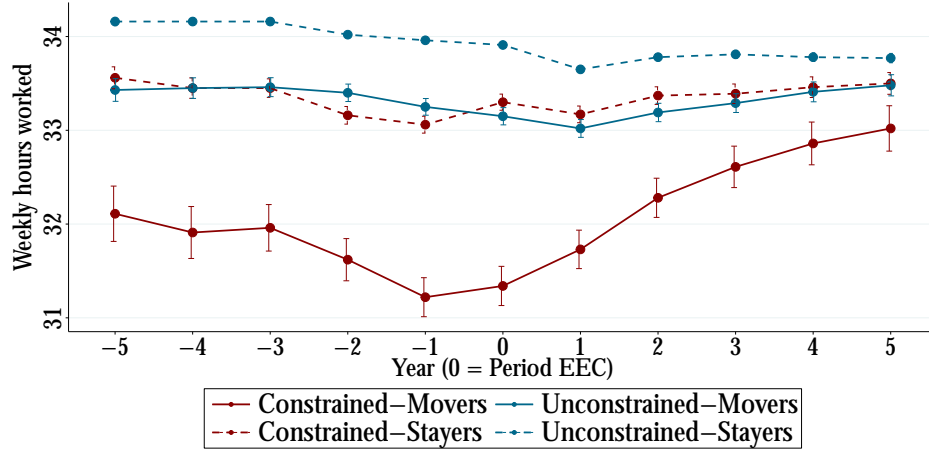
5.2 Event-Study Design

Here, I study the evolution of constrained workers as compared to unconstrained workers using a more formalized approach. Given that constrained workers are mostly able to adjust their hours by switching firms, I estimate the differential change in outcome associated with employer-to-employer mobility for both types of workers. I use an event-study design summarized by the following equation:

$$y_{it} = \beta_1 \times S_{it} + \beta_2 \times S_{it} \times C_i + \alpha_i + \gamma_t + \varepsilon_{it} \tag{5}$$

The considered outcomes y_{it} are hours worked, hourly wages, and earnings (in logs). S_{it} is a dummy variable equal to 1 if the individual i is a *"mover"* in year t, where t must be between 1 and 3 years after the EEC period. This restriction on considered moves favors their consistency

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[18]The sample divides across the four groups as follows: 5.2%, 16.0%, 14.3%, and 64.5%.

Figure 6: Evolution of Hours in the EEC-DADS Panel

Note: This figure represents the evolution of weekly hours across employer-to-employer transitions for different worker groups. The x-axis shows years relative to the EEC period, while the y-axis displays average weekly paid hours worked from the DADS. The data used is the EEC-DADS Panel (see Section 3.3 for details). Four distinct groups are tracked: constrained-movers (solid red line), unconstrained-movers (solid blue line), constrained-stayers (dashed red line), and unconstrained-stayers (dashed blue line). Workers are classified as constrained or unconstrained based on their reported hour preferences in the last quarter of the EEC period, and as movers or stayers based on whether they switch employers during years 1 to 3 after the EEC period. Error bars correspond to 95% heteroskedasticity-robust confidence intervals.

with hours preferences reported in the EEC[19]. C_i is a dummy variable equal to 1 if the individual i is constrained in the last quarter of their EEC period. α_i and γ_t are respectively worker-specific and year-specific fixed effects. β_1 captures the effect on the outcome associated with employer-to-employer moves. β_2 measures the differential effect for constrained workers. Worker fixed effects are included to control for time invariant unobserved heterogeneity. The sample gather all moves that occur between the EEC period and up to 3 years after it. This corresponds to 32,269 employer-to-employer moves over a sample of 157,716 workers, with constrained workers covering 20% of moves.

Event-study designs are a widely used method for estimating treatment effects. Their validity in capturing causal effects yet relies on two critical identifying assumptions: no-anticipation and parallel trends (Borusyak et al., 2024). The no-anticipation assumption requires that workers do not change their behavior before switching jobs, while the parallel trends assumption holds if workers who change employers or stay would have followed similar trajectories in outcome absent mobility. To test the validity of the assumptions, I examine the similarities of movers and stayers groups in trend during the pre-event window. Figure A6a plots event-study coefficients

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[19]In addition, in the case where the individual experiences multiple transitions shortly after the EEC period, I only consider the first move as it is the one consistent with reported hours preferences.

associated with moves on hours worked following Callaway and Sant'Anna (2021)[20] and provides direct evidence of violations. The pre-event coefficients, though modest in size compared to the post-event ones, are significantly different from zero and show a notable decline in hours just before the move. This pre-move drop suggests that workers whose hours are decreasing are more likely to switch employers. Figure A6b shows the equivalent coefficients for the interaction term by comparing constrained and unconstrained workers who switch firms. Both groups exhibit similar pre-trends in hours, suggesting that being constrained is not associated with different prior evolution of hours conditional on being a mover. From a broader perspective, the parallel trends assumption is not credible here as both employer-to-employer moves and worker preferences are likely endogenous to prior dynamics in working hours. Then, estimates from Equation 5 cannot be interpreted as treatment effects of mobility. Hence, I use the event-study framework as a descriptive tool, as it provides a clear and intuitive quantification of how working hours of constrained and unconstrained workers diverge around employment transitions.

Table 4 reports estimates from Equation 5. Coefficients are estimated separately by working time status during the EEC period. The first row shows the effects associated with employer-to-employer moves for unconstrained workers. For this group of workers, I find that switching firms is associated with a 2.4% increase in hours among part-time workers, driven by a 13 pp higher probability to move full-time, but does not correlate with the evolution of hours among full-time workers. Both types of unconstrained movers yet experience a relative decrease in wages, which leads to a significant reduction in earnings for full-time workers. Negative changes in earnings associated with employer-to-employer mobility may surprise, as they reflect that workers would quit a job for another job that pays less. This result is yet consistent with previous findings by Babet and Chabaud (2024) who study wage dynamics of individuals who switch employers using the same data. In their paper, they show that cuts in annualized earnings across firm-to-firm mobility are very frequent, even when restricting to voluntary moves[21]. Following the approach by Sorkin (2018), they find that non-wage amenities account for about 10% of the variance in log wages, where working hours are included in amenities. My approach complements their paper by allowing to distinguish between workers who intend to increase their earnings by working more hours and those who do not. Estimates from Table 4 suggest that workers who have no

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[20]The control group is composed of non-movers, i.e. *never-treated* individuals.

[21]Voluntary moves are defined as moves out of a permanent contract (*CDI*) that did not involve a significant unemployment spell. This definition of moves is used as a robustness check in Section 5.5 and implies a positive shift on estimates of unconstrained movers for every outcome. In particular, the negative coefficient on earnings in the full-time sample shrinks but remains significantly negative ($\beta = -0.008^{**}$).

specific interest in increasing their hours can experience reduction in earnings through mobility, most likely because of other non-wage amenities.

Table 4: Event-Study Effects on Hours, Wages and Earnings

Group (EEC Period):	**Part-Time**			**Full-Time**		
Dependent Variable (in logs):	Hours (1)	Wages (2)	Earnings (3)	Hours (4)	Wages (5)	Earnings (6)
Mover	0.024*** (0.009)	-0.039*** (0.004)	-0.016 (0.009)	-0.002 (0.002)	-0.046*** (0.001)	-0.048*** (0.002)
Mover × Constrained	0.063*** (0.015)	-0.009 (0.007)	0.055*** (0.014)	0.008* (0.004)	0.004 (0.003)	0.012** (0.004)
Fixed effects						
Worker FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
Baseline (in levels)	25.4	13.8	18,341	34.6	16.5	29,595
Observations	60,413	60,413	60,413	483,266	483,266	483,266
Adj. R^2	0.78	0.89	0.88	0.60	0.93	0.90

Signif. Codes: ***: 0.001, **: 0.01, *: 0.05.
Note: This table presents estimates from event-study regressions specified in equation 5. The data used is the EEC-DADS Panel between 2003 and 2023 (see Section 3.3 for details). The first three columns of the table correspond to estimates when restricting the sample to workers who primarily worked as part-time during the last year of their EEC period. The last three columns correspond to results in the equivalent full-time sample. The dependent variables are respectively the logs of weekly hours, hourly wages and net annual labor earnings from the DADS data. Hours are paid hours recomputed as full-year equivalent and divided by 52. Earnings are also recomputed as full-year equivalent based on the number of days worked over the year. "Mover" is a dummy variable equal to 1 if the worker's primary employer is different than the year before. The primary employer is defined as the one with highest annual earnings. In addition, moves used for the estimation must occur between 1 and 3 years after the EEC period. "Constrained" is a dummy variable equal to 1 if the worker is constrained (from above) in their hours in the last year of their EEC period. Worker fixed effects (Worker FE) control for time-invariant unobserved heterogeneity. Year fixed effects (Year FE) control for common time trends. Standard errors are heteroskedasticity-robust and reported in parentheses.

The second row of Table 4 reports differential changes associated with employer-to-employer mobility for constrained workers, the primary focus of this paper. Estimates show that mobility is associated with relative positive effects in hours and earnings for constrained, consistently with graphical evidence from Figure 6. Constrained part-time workers who switch employers experience a 6.3% relative increase in hours as compared to unconstrained movers, which sums to a 8.7% increase compared to non-movers, driven by a 17 pp higher probability to move to a full-time job. As a result, their earnings increase 5.5% more than unconstrained movers and 3.9% more than non-movers, due to negative wage changes of the same order of magnitude as unconstrained workers. Hence, employer-to-employer mobility appears as an effective way for constrained workers to increase their revenues. Conversely, constrained workers in the full-time group experience small increases in hours and earnings, of magnitude 0.8% and 1.2%, relative to unconstrained movers. The combination of both coefficients implies a 3.6% reduction in earnings

for constrained movers as compared to baseline non-movers.

Figure A7 explores underlying heterogeneity behind the main estimates. I split the sample by workers' broad occupation during the EEC period, where occupations correspond to the first digit of the PCS classification (4 values). Estimates on hours for constrained part-time workers are primarily driven by tertiary low and mid-skill occupations. For example, workers in low-skill non-manual occupations experience an 11% increase in hours relative to non-movers, significantly larger than the 4.5% increase for their unconstrained counterparts, and a 7% relative increase in earnings. This finding is particularly important as this group represents 55% of the sample of constrained part-time workers. For full-time workers, mid-skill workers tend to experience slightly larger hours adjustments, but no occupation really stands out.

To summarize, employer-to-employer mobility is a particularly effective way for part-time workers to adjust their hours and boost their earnings. Conversely, full-time workers who report wanting to work more experience a similar evolution than other full-time workers. This contrast suggests that part-time workers may have more stringent preferences, i.e. their disutility from being underemployed may be larger than it is for full-time workers. Another potential explanation is that full-time workers cannot easily increase their hours as overtime hours are rarely advertised by employers[22]. In the rest of the section, I provide complementary findings on the labor market trajectories of constrained workers.
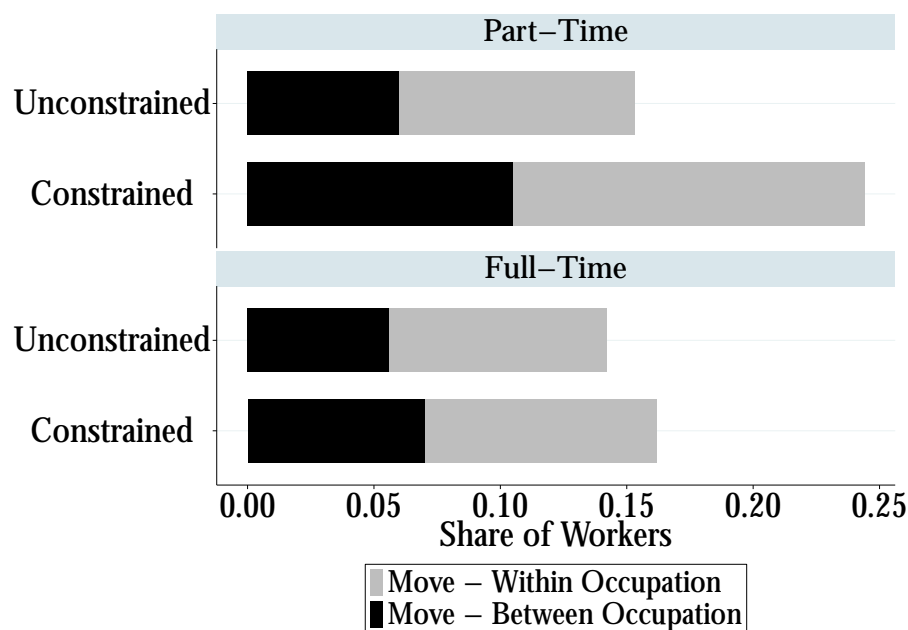
5.3 Adjustment Mechanisms

This part examines what types of mobility enable largest adjustments in hours for constrained workers. Typically, I study whether positive changes in hours mostly occur when workers remain in their current occupation or switch to a new one. Thereby, I provide additional evidence into the underlying structure of hours constraints.

Figure 7 presents the distribution of employer-to-employer moves for constrained and unconstrained workers by working time status. I classify movers into two categories based on their first move after the EEC period: those who remain in the same occupation (*within-occupation*) and those who switch to a new one (*between-occupation*). In this section, occupations correspond to the 2-digit level in the PCS classification (28 values), so that a between-occupation move reflects a transition towards a non-similar job. As already noted in Table 3, constrained workers exhibit a

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[22]Only one third of employer-to-employer mobilities by full-time workers induces an increase of more than one hour per week.

higher propensity to switch firms, especially among part-time workers. Conditional on moving, constrained and unconstrained workers are relatively similar in their distribution across groups. Section 4.1 showed the strong concentration of constrained part-time workers in few occupations. This suggests that workers may need to switch occupations to increase their hours, aligning with previous work by Altonji and Paxson (1986). If this is true, between-occupation moves should generate larger hours increases than within-occupation moves. To test this, I re-estimate coefficients from Equation 5 separately for workers who stay in their occupation and those who switch occupations, while still using non-movers as the comparison group.

Figure 7: Types of Mobility

Note: This figure displays the distribution of job-to-job transitions by type of mobility for constrained and unconstrained workers, separately for part-time and full-time employees. The data used is the EEC-DADS Panel (see Section 3.3 for details) and includes moves occurring between 1 and 3 years after the EEC period. When workers experience multiple transitions during this window, only the first is retained. Black bars represent within-occupation moves (workers who change employers while remaining in the same occupation), while gray bars represent between-occupation moves (workers who change both employer and occupation). Occupations correspond to the 2-digit level in the PCS classification (28 values). The horizontal axis shows the share of workers in each category.

Table 5 presents event-study estimates by mobility type. Among part-time workers, switching occupations generates substantially larger increases in hours worked than remaining in the same occupation: 4.5% versus 1.1% for unconstrained workers, and 11.1% versus 6.5% for constrained workers. This difference arises primarily because occupation switchers are considerably more likely to transition to full-time employment (15 percentage points more for unconstrained workers and 11 percentage points more for constrained workers). Consequently, between-occupation

moves yield significant earnings gains, while within-occupation moves do not. For full-time workers, within-occupation moves produce similar outcomes for both constrained and unconstrained workers. In contrast, constrained workers who switch occupations tend to increase their hours and earnings relative to their unconstrained counterparts. However, this pattern rather reflects large declines in outcomes among unconstrained workers who switch occupations. The net effect for constrained workers is only a modest increase in hours, which fails to offset the substantial wage decline.

Table 5: Event-Study Effects By Occupational Mobility

Group (EEC Period):	**Part-Time**			**Full-Time**		
Dependent Variable (in logs):	Hours (1)	Wages (2)	Earnings (3)	Hours (4)	Wages (5)	Earnings (6)
Panel A: Within-Occupation						
Mover	0.011	-0.025***	-0.013	0.004	-0.029***	-0.026***
	(0.010)	(0.005)	(0.010)	(0.002)	(0.002)	(0.002)
Mover × Constrained	0.054**	-0.013	0.041*	-0.000	0.002	0.002
	(0.017)	(0.008)	(0.017)	(0.005)	(0.004)	(0.005)
Fixed effects						
Worker FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
Observations	55,075	55,075	55,075	444,611	444,611	444,611
Adj. R^2	0.80	0.90	0.89	0.61	0.93	0.91
Panel B: Between-Occupation						
Mover	0.045**	-0.063***	-0.018	-0.010**	-0.071***	-0.081***
	(0.016)	(0.008)	(0.016)	(0.003)	(0.002)	(0.004)
Mover × Constrained	0.076***	0.002	0.078**	0.019**	0.011*	0.030***
	(0.026)	(0.012)	(0.026)	(0.007)	(0.005)	(0.008)
Fixed effects						
Worker FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
Observations	52,580	52,580	52,580	427,943	427,943	427,943
Adj. R^2	0.67	0.77	0.74	0.53	0.85	0.80

*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05.*
Note: This table presents estimates from event-study regressions specified in equation 5 considering within-occupation and between-occupation moves separately. The data used is the EEC-DADS Panel between 2003 and 2023 (see Section 3.3 for details). Panel A restricts the sample to non-movers and within-occupation movers (workers who change employers while remaining in the same occupation). Panel B restricts the sample to non-movers and between-occupation movers (workers who change both employer and occupation). Occupations correspond to the 2-digit level in the PCS classification (28 values). See Table 4 for details.

The large changes in hours experienced by constrained part-time are primarily driven by occupational switches along employer-to-employer mobility. This pattern might suggest the existence

of occupational rigidities in hours, whereby workers adjust their hours by moving to occupations with longer hours requirements. However, the evidence does not support this interpretation: only 58% of between-occupation moves by constrained workers involve a shift to occupations with higher fixed effects for hours, compared to 51% for unconstrained workers. Thus, the occupational composition of employer-to-employer moves does not primarily explain the results. Moreover, the direction of the move in terms of occupational fixed effects is not always relevant. For constrained part-time workers, hours increase by 16.5% when moving to a higher-FE occupation ($\uparrow h_{PCS}$) and by 12.7% when moving to a lower-FE occupation ($\downarrow h_{PCS}$). The distinction matters more for constrained full-time workers: moves to higher-FE occupations are associated with a significant 3.1% increase in hours, while moves to lower-FE occupations show no significant effect. Hence, constrained workers of both working time status exhibit different mobility patterns. In particular, constrained part-time workers appear to move whenever they find a job with longer hours, regardless of whether the occupation has high or low hours requirements.

Then, I use a similar approach based on firms' hours policies, measured by AKM firm effects on hours[23]. I include both within-occupation and between-occupation moves and split them into two groups based on whether workers move to a firm with a higher ($\uparrow h_{AKM}$) or lower ($\downarrow h_{AKM}$) AKM firm effect than their origin firm. Constrained and unconstrained part-time workers are distributed similarly across these two types of moves: 60% versus 54% move to firms with a higher AKM firm effect. Figure A8 plots estimates for all types of mobility based on occupation or firm FE. Strikingly, for all types of workers, moving to a firm with a higher AKM effect increases hours worked, while moving to a firm with a lower effect produces negative or no change in hours. Constrained part-time workers who move to higher h_{AKM} firms experience a 17% increase in hours, which fully accounts for the baseline 8.7% estimate from Table 4. These results align with the earlier findings from Section 4.2 about the importance of firm effects in hours constraints.

5.4 Reaching Desired Hours

Ultimately, constrained workers aim to circumvent their hours constraints and find a job that better suits their hours preferences. In this part, I study to what extent workers are able to reach their self-reported desired hours shortly after the EEC period.

I restrict the EEC-DADS Panel to constrained workers and use workers' self-reported ideal hours to measure the share of workers who work fewer hours than their ideal level up to 3 years
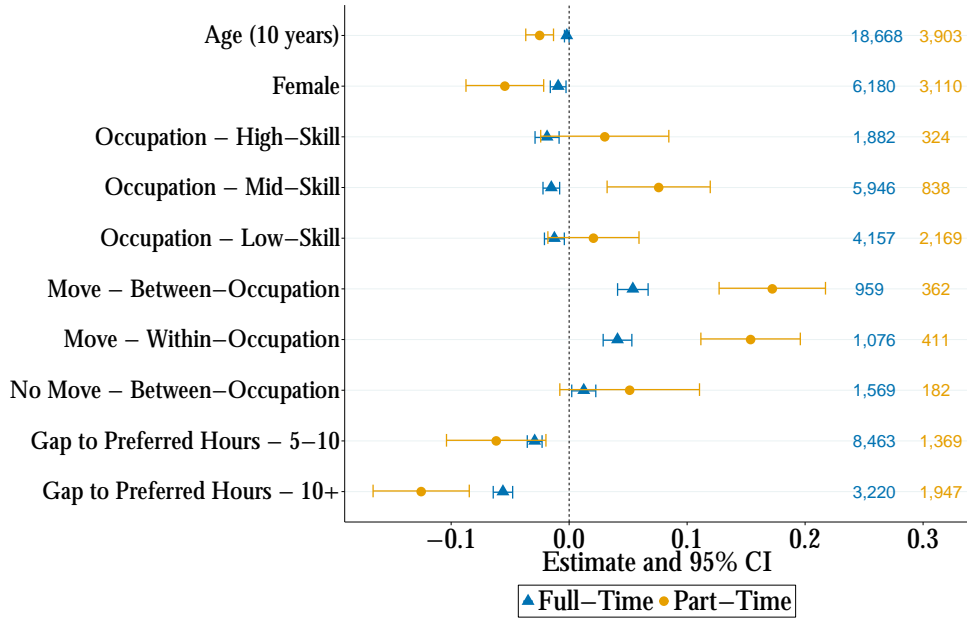
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[23]See Section 4.2 for details about the estimation.

after the EEC period. The sample is composed of 22,571 individuals. I find that most workers do not increase their hours to their desired level. After three years, 18% of constrained part-time workers have closed the gap, compared to 4% of full-time workers. This difference reflects disparities in the ability to adjust hours, as discussed in previous sections. Full-time workers are less prone to adjustments because of the limited variation in hours across full-time jobs. The proportion of workers who reach their desired hours declines each year, which could suggest that workers who are unable to adjust their hours in the short-run will remain in a short-hour trap for the next years. This underscores that only a limited share of constrained workers can adjust their hours to their ideal level, hence tempering previous estimates that reflect large hours increases for constrained workers.

Since the underlying goal of constrained workers is often higher earnings (as shown in Figure B1b), workers may also achieve their goal by an adjustment in hourly wages rather than hours. To assess this, I compute implicit desired earnings as the product of the hourly wage in the EEC period and desired hours. The shares of workers who reach this level of earnings are 25% in the part-time group and 28% in the full-time group, relying on an average 20% increase in hourly wages. This suggests that circumventing hours constraints builds on the combination of adjustments both in hours and earnings. Yet, even considering earnings, constrained workers who are able to find a job that suits their preferences remain a minority.

Next, I tackle the heterogeneity in reaching desired hours. For each working time status, I regress a dummy variable equal to one if the individual has reached their desired hours level within three years after the EEC period on various covariates included jointly. Figure 8 shows the estimates for each covariate. The number of constrained workers is reported on the right of the plot. Age and being a woman both reduce the probability of reaching their desired hours, particularly among part-time workers. Occupation plays a differential role across groups: among part-time workers, mid-skill workers are significantly more likely to adjust their hours as compared to low-skill manual workers (the reference group), while among full-time workers, low-skill manual workers are more likely to adjust than any other group. As explained in Section 5.2, employer-to-employer moves are the most effective mechanism to increase hours to the desired level. Finally, constrained workers with smaller gaps between actual and desired hours are, logically, more likely to attain their desired level.

Figure 8: Probability to Reach Desired Hours

Note: This figure shows coefficient estimates from separate regressions for part-time and full-time constrained workers. The dependent variable is an indicator equal to one if the worker has reached their desired hours level within three years after the EEC period. All covariates are included jointly. Numbers on the right indicate the sample size for each group. Reference categories for categorical variables are low-skill manual workers, workers who do not move and remain in the same occupation and gaps to desired hours of less than 5 hours. Occupations correspond to the 2-digit level in the PCS classification (28 values). Error bars correspond to 95% confidence intervals.

5.5 Robustness Checks

This section evaluates whether three potential measurement issues affect the validity of the results. Reassuringly, the main findings remain overall robust across alternative specifications.

Voluntary Moves. The interpretation of job moves as reflecting revealed preferences relies on the assumption that these moves are voluntary. To test this, I re-estimate the main specification from Equation 5 using a stricter definition of mobility. A move is classified as voluntary if it originates from a permanent contract and involves less than 60 days between jobs[24]. Table A4 reveals meaningful differences from the original specification. Voluntary moves are associated with larger hour increases (5.9% for part-time and 1.5% for full-time workers) and smaller wage reductions. As a result, the combined effect on earnings becomes significantly positive for part-time workers and only slightly negative for full-time workers. For constrained part-time workers specifically, voluntary moves enable a 15% increase in hours and a 10% increase in earnings compared to those

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[24]This definition differs slightly from Babet and Chabaud (2024), as I use the starting and ending dates of employment rather than unemployment benefit receipts to determine the no-unemployment criterion.

who remain with the same employer. Conversely, among full-time workers, voluntary moves produce similar effects for both constrained and unconstrained workers. In addition, moves that are not classified as voluntary do not imply significantly different changes in outcome for constrained and unconstrained workers for both working time status. This provides support for the argument that positive changes in hours for constrained workers reflect revealed preferences.

Persistent Hours Preferences.   As discussed in Appendix B2, workers' hours preferences show limited persistence over time. This raises the possibility that hours constraints measured during the EEC period may not persist afterward—meaning some constrained workers may no longer wish to increase their hours in subsequent periods. To address this concern, I restrict the sample of constrained workers to those whose preferences remain identical throughout their EEC period, thereby focusing on workers with stable preferences for longer hours. Table A5 shows results broadly similar to the original specification. Estimates for unconstrained workers remain nearly unchanged as their sample is unaffected by the restriction. For constrained workers, the interaction coefficients on hours and earnings are attenuated for part-time workers but roughly doubled for full-time workers. This suggests that distinguishing between workers with stable versus unstable preferences is particularly important for understanding full-time worker behavior.

Period-Specific Estimates.   To address the concern that the estimates may be driven by specific time periods, I split the sample into four subsamples, each excluding a different five-year period, and re-estimate the main results. Table A6 shows a remarkable consistency in estimates across panels for constrained workers. The primary exception is a notable decrease in the hours and earnings coefficients for part-time workers when the 2019–2023 period is excluded. This suggests that constrained part-time workers have increasingly moved towards longer hours in recent years, consistent with the view that hours constraints are an important contemporary phenomenon.

Amenities.   To limit the role of other job amenities, I re-estimate the main specification restricting the sample to movers who increase their commuting distance by less than 10 kilometers (or reduce it). Distances between municipalities are calculated using the Haversine formula, which computes the great-circle distance between two points on a sphere given their latitude and longitude coordinates. Table A7 displays the estimates of this new specification. As compared to the original specification, mobilities of unconstrained movers tend to be associated with slightly more positive changes in hours and earnings. On the other hand, the interacted coefficients are smaller

so that the combined effect is similar in magnitude to the previous estimates. Results suggest that distance to work affects more unconstrained than constrained workers in their employer-to-employer moves.

6 Willingness-To-Pay

This section aims to identify workers' willingness-to-pay (WTP) to relax hours constraints building on the approach of Le Barbanchon et al. (2020). The goal of the estimation is to quantify in monetary terms how strong are workers' preferences to reach their desired hours.

6.1 Framework

We start from the framework introduced in Section 2. Worker utility is $u(w, h) = wh - \varepsilon h^\mu$ as in Lachowska et al. (2023), where ε captures preferences for leisure and μ measures disutility from working, with $\mu > 1$. Workers are asked (as in the EEC) to report their optimal level of hours h^* at their given wage level w_0. Given this framework, the willingness-to-pay can be expressed as the difference between the current wage and the wage that would provide the same utility level when working optimal hours:
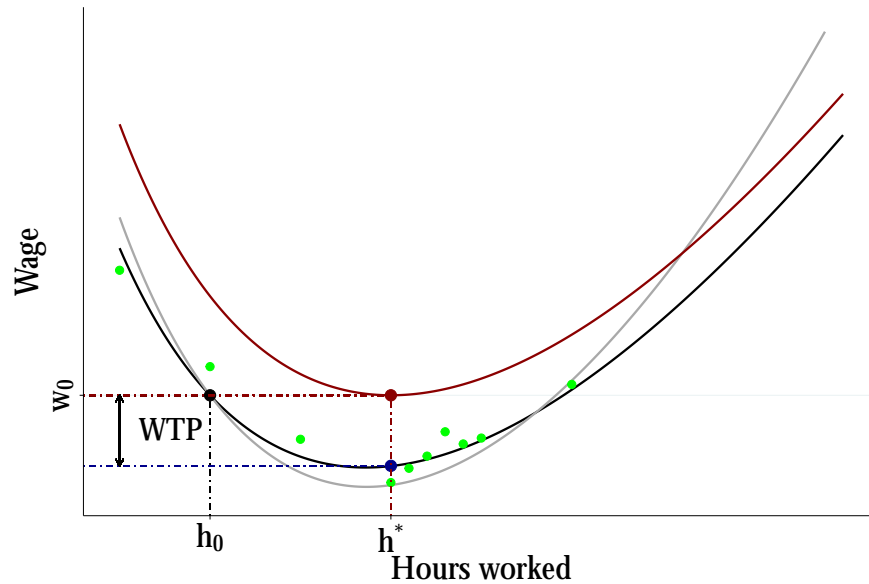
$$\theta = w_0 - w\big(u(h_0, w_0), h^*\big) \tag{6}$$

This corresponds to the absolute reduction in hourly wage that a worker would accept to work their desired number of hours. Note that the counterfactual bundle $(w\big(u(h_0, w_0), h^*\big), h^*)$ must yield higher earnings than (h_0, w_0), as the reduction in hourly wage is compensated by an increase in hours worked. Consider the following example to illustrate the concept. An individual works 20 hours per week for 200€ weekly earnings and reports wanting to work 40 hours per week with a corresponding variation in income, leading to a virtual increase in earnings to 400€ per week. It is yet plausible that this worker would accept to work 40 hours per week for less than 400€, as this would still imply a large increase in earnings. The question that the estimation aims to answer is how much less. If the accepted threshold amount is 360€, then the WTP to work 40 hours per week is equal to: $\frac{400-360}{40} = 1$€/hour, that is 10% of the initial hourly wage. In short, the expression "willingness-to-pay" is to be understood in terms of hourly wage rather than total earnings. Workers are observed for a number of periods after their report (as in the EEC-DADS Panel). In particular, they can decide to move to a different job with wage-hour bundle (h_l, w_l). The

method by [Le Barbanchon et al. (2020)](#) fits the parameters of the iso-utility curve by minimizing a loss function corresponding to the Euclidian distance between destination job bundles (h_l, w_l) that are below the current job's iso-utility curve and their linear projection on this curve. The intuition is to draw the iso-utility curve that best rationalizes the acceptance of destination jobs from the revealed preference criterion: $u(h_l, w_l) > u(h_0, w_0)$.

Figure [9](#) illustrates the strategy. Black and grey curves are two potential iso-utility curves, i.e. representing the space of wage-hour bundles that yield the same utility as the initial bundle (h_0, w_0), with different values of ε and μ. Likewise, the red curve corresponds to the level of utility derived from the optimal bundle (h^*, w_0). Green dots correspond to all destination job bundles for individuals with the initial job bundle (h_0, w_0) and optimal hours h^*. The goal of the method is to estimate ε and μ, the parameters of the utility function, in order to recover the y-axis coordinate of the blue point and compute the WTP. In this example, the black curve is the curve that satisfies the minimization problem, as the grey curve implies a higher distance.

Figure 9: Willingness-To-Pay Framework

Note: The figure illustrates the framework for estimating willingness-to-pay (WTP) to relax hours constraints. The initial job bundle (h_0, w_0) and the worker's optimal hours h^* are shown. Black and grey curves represent potential iso-utility curves through (h_0, w_0) with different parameter values in the utility function $u(h, w) = wh - \varepsilon h^\mu$. The red curve shows the iso-utility curve through the optimal bundle (h^*, w_0). Green dots represent observed destination job bundles (h_l, w_l). The estimation method identifies utility parameters by minimizing the Euclidean distance between destination bundles below the iso-utility curve and their projections onto it. The black curve best fits the observed transitions. WTP is the vertical distance between the blue point at h^* and w_0, representing the wage reduction a worker would accept to work optimal hours while maintaining utility.

The optimality of the bundle (h^*, w_0), i.e. at this point the marginal utility is 0, allows to write

ε with respect to μ, thus to reduce the optimization problem to one parameter.

$$\left.\frac{\partial u}{\partial h}\right|_{h=h^*,w=w_0} = 0 \Leftrightarrow w_0 - \mu\varepsilon h^{*\mu-1} = 0 \Leftrightarrow \varepsilon = \frac{w_0}{\mu h^{*\mu-1}} \tag{7}$$

The optimization problem then becomes almost identical to Le Barbanchon et al. (2020)'s estimation of the slope parameter in the wage-commute plane. Denote $\mathcal{B}_\mu$ the set of destination job bundles below the current job's iso-utility curve ($\mathcal{B}_\mu = \{l \mid u(h_l, w_l) < u(h_0, w_0)\}$). The target estimator of the parameter can then be written as:

$$\hat{\mu} = \operatorname{argmin}_\mu \sum_{l \in \mathcal{B}_\mu} d_{\mu,h_0,w_0}(h_l, w_l)$$
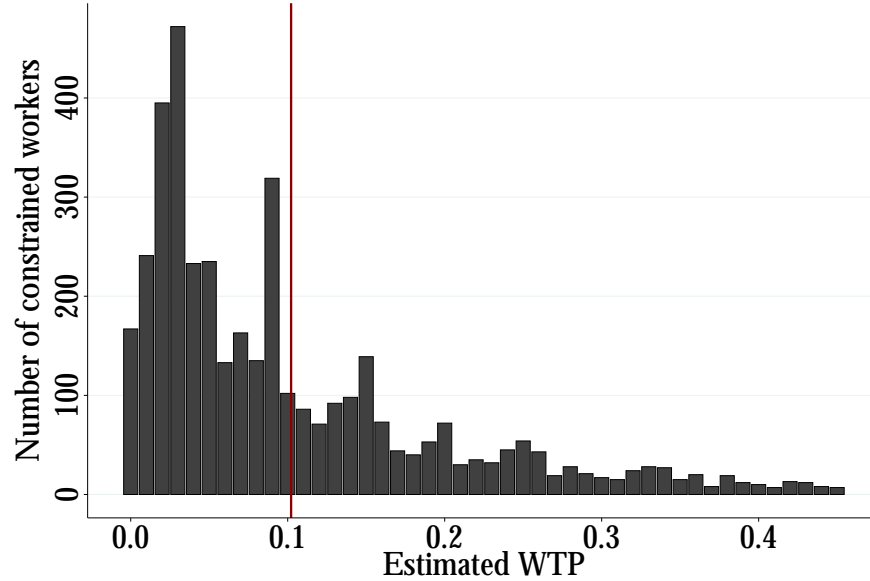
6.2 Estimation

This section describes the implementation of the strategy. I restrict the EEC-DADS Panel to workers constrained (from above) who switch firms between 1 and 3 years after the EEC period starting from a permanent contract. This yields a sample of 3,926 workers. As in previous sections, in the case where a worker moves multiple times over this period, I restrict to the first move to ensure consistency with reported hours preferences.

I solve the optimization problem by using a grid search approach. The approach identifies $\hat{\mu}$, the μ that minimizes the Euclidean distance between the indifference curve at (h_0, w_0) and bundles that are below this curve. The procedure then takes place in the following steps, considering μ as given: (a) For each worker, characterized by their initial bundle (h_0, w_0) and optimal hours h^*, I derive ε from Equation 7. With μ and ε known, I can represent the iso-utility curve at the initial bundle ; (b) I identify all downward-utility moves, i.e. all moves to a destination bundle (h_l, w_l) that yields a utility level inferior to $u(h_0, w_0)$, thereby building the set $\mathcal{B}_\mu$ for this value of μ ; (c) For each identified bundle, I compute the Euclidean distance between the bundle and the closest point on the initial iso-utility curve[25]. The distance is given by $\sqrt{(h_l^p - h_l)^2 + (w_l^p - w_l)^2}$; (d) The loss function that is minimized is the sum of distances across workers of the sample: $\sum_{l \in \mathcal{B}_\mu} \sqrt{(h_l^p - h_l)^2 + (w_l^p - w_l)^2}$. Once $\hat{\mu}$ is identified, each worker's willingness-to-pay can be recovered as the vertical distance between w_0 and the initial iso-utility curve at hours h^* (see Equation 6). The procedure is conducted for each hundredth value of μ between 1.01 and 10.

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[25]This closest point (h_l^p, w_l^p) is found by solving for the point on the iso-utility curve where the derivative of the squared distance with respect to hours equals zero.

The grid search estimation yields $\hat{\mu} = 5.76$. Figure 10 shows the distribution of willingness-to-pay estimates for workers to reach their desired hours, relative to their initial wage w_0. The estimates are particularly concentrated between 0 and 10%, and the average (represented by the vertical red line) is equal to 10.2%. Consistently with previous results, the average WTP is higher for part-time, 15.9%, than for full-time workers, 9.4%. This is a consequence of larger gaps to desired hours among part-time workers, given that most of them would ideally move to a full-time job. Bootstrapped standard errors of these estimates should be provided in a further version of the paper.

Figure 10: Willingness-To-Pay Estimates

Note: The figure represents the distribution of estimates of the workers' willingness-to-pay to reach their self-reported desired hours. The sample consists of 3,926 constrained workers from the EEC-DADS Panel. See the text for details on the estimation procedure.

The average estimate of 10.2% cannot be directly compared with the 12% result from Lachowska et al. (2023). Their measure corresponds to the relative increase in wages required by workers to be as well as they would be after moving to an employer offering ideal hours. This corresponds in Figure 9 to the distance between the initial bundle (h_0, w_0) and its vertical projection on the red iso-utility curve. In the present framework, it can be expressed as:

$$\theta_{alt} = w\big(u(h^*, w_0), h_0\big) - w_0$$

The average estimate of this alternative definition is 16.6%. This definition of the willingness-to-

pay yields a higher estimate because it implicitly relies on a smaller number of hours, h_0 rather than h^*. Since h^* is the preferred number of hours, the counterfactual utility change that drives the willingness-to-pay must be achieved by a higher variation in hourly wages when starting from h_0, a lower undesired level. Then, their measure is always superior for a given worker who is constrained from above[26]. This estimation of the willingness-to-pay relies on a different method in a different labor market but the orders of magnitude of the estimates are similar. Overall, estimates point towards the interpretation of hours constraints as associated with large welfare costs across the workforce.

7 Conclusion

This paper leverages a unique data linkage to produce novel empirical evidence on hours constraints in France. By combining self-reported hour preferences from the Labour Force Survey with administrative employer-employee records, I show that hours constraints play a significant role in labor market dynamics. The analysis highlights the central role of firms in generating these constraints and provides the first evidence on workers' ability to adjust their hours through employer-to-employer transitions. In the final section, I estimate workers' willingness to pay to reach their desired hours, revealing non-negligible welfare costs associated with hours constraints.

These findings shed new light on underemployment, a multi-dimensional problem in modern labor markets that, like unemployment, stems from the interaction of worker-specific characteristics and firm-level factors. Involuntary part-time workers emerge as the most precarious group, unable to supply the same number of hours as most workers despite their willingness to do so. Understanding the firm's role in hours determination is essential for designing effective interventions to reduce underemployment and improve labor market matching.

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[26]See Appendix C.2 for the proof.

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Appendix A   Additional Figures and Tables

A.1   Tables

Table A1: EEC and Matched EEC-DADS Samples, 2003-2023

		EEC Sample	EEC Sample (with *SIRET*)	EEC-DADS Sample	EEC-DADS Panel
Number of observations		3,201,635	2,619,074	1,695,359	9,734,018
Number of workers		791,701	654,632	435,472 (67%)	399,553 (61%)
Number of firms		262,823	262,823	196,484	612,603
Full-Time (%)		81.0	82.7	82.8	82.8
Female (%)		50.4	49.3	48.4	49.4
Age	15-24	8.3	8.1	8.5	13.4
	25-34	20.6	20.8	21.3	24.6
	35-44	26.0	26.3	26.9	25.1
	45-54	28.3	28.4	27.9	24.1
	55+	16.7	16.3	15.5	12.8
Occupation (%)	High-Skill	17.4	18.1	17.3	17.4
	Mid-Skill	26.4	27.5	27.3	26.4
	Low-Skill Non-Manual	32.2	30.2	28.8	30.4
	Low-Skill Manual	24.0	25.0	26.6	25.7
Firm Size (%)	< 10	59.1	57.6	58.2	58.7
	10-49	15.4	16.0	16.6	17.3
	50-499	17.3	18.1	18.2	17.5
	≥ 500	8.2	8.3	7.0	6.5
Usual Hours Worked (%)	< 25	10.4	9.0	8.6	11.8
	25-34	10.0	9.9	9.7	10.0
	35-39	52.5	55.1	55.9	53.0
	40-49	19.5	18.9	18.9	18.0
	≥ 50	7.6	7.1	7.0	7.2
Share of constrained from above - Full-Time (%)		16.3	16.9	19.0	19.5
Share of constrained from above - Part-Time (%)		34.7	33.8	26.0	23.8
Share of involuntary part-time workers (%)		24.2	24.3	19.0	17.1
Share of constrained from below (%)		2.4	2.5	2.5	2.5

Note: This table compares the two newly built EEC-DADS and EEC-DADS Panel samples with the original EEC sample. The EEC sample (with *SIRET*) corresponds to the EEC sample after removing observations where the establishment's ID is missing. Shares of constrained and involuntary part-time workers are computed in proportion of the corresponding working time status considering the workers' last quarter of observation.

Table A2: Summary Statistics of Constrained Workers in EEC-DADS and EEC

Variable	Involuntary Part-Time		Full-Time	
	EEC	EEC-DADS	EEC	EEC-DADS
Age - 15-24 (%)	37.1	38.1	37.8	37.5
Age - 25-34 (%)	37.1	38.1	37.8	37.5
Age - 35-44 (%)	37.1	38.1	37.8	37.5
Age - 45-54 (%)	37.1	38.1	37.8	37.5
Age - > 55 (%)	37.1	38.1	37.8	37.5
Female (%)	73.8	71.8	61.5	58.6
Occupation - High-Skill (%)	4.0	4.6	10.8	9.9
Occupation - Mid-Skill (%)	16.4	12.7	27.8	22.1
Occupation - Low-Skill Non-Manual (%)	58.3	60.0	27.4	31.1
Occupation - Low-Skill Manual (%)	21.4	22.7	33.9	36.9
Born Abroad (%)	13.8	12.7	10.8	10.5
Public Sector (%)	23.7	19.6	17.6	13.0
Permanent Contract (%)	58.4	71.7	83.3	83.2
Usual Hours Worked	23.3	26.4	37.3	35.6

Note: This table presents summary statistics of constrained workers in the EEC and EEC-DADS samples. "Occupation" categories correspond to the 1st-digit in the PCS classification, respectively 3, 4, 5 and 6. "Born Abroad" indicates the proportion of individuals born outside of France. "Public Sector" shows the proportion of workers in the public sector. "Permanent Contract" represents the share of workers with a permanent contract (*contrat à durée indéterminée*). Hours worked correspond to usual hours worked from the Labour Force Survey.

Table A3: Summary Statistics by Group of Workers' Preferences

Variable	Constrained from above	Involuntary part-time	Constrained from below	Unconstrained
Age - 15-24 (%)	10.9	14.8	1.8	5.5
Age - 25-34 (%)	28.4	23.6	19.2	20.2
Age - 35-44 (%)	28.3	25.9	28.9	27.2
Age - 45-54 (%)	24.3	25.7	32.5	30.4
Age - > 55 (%)	8.2	10.0	17.6	16.7
Female (%)	48.7	77.2	61.2	49.1
Occupation - High-Skill (%)	8.9	4.6	31.4	20.2
Occupation - Mid-Skill (%)	24.9	16.0	32.2	28.3
Occupation - Low-Skill Non-Manual (%)	37.1	60.9	24.6	28.8
Occupation - Low-Skill Manual (%)	29.1	18.5	11.8	22.6
Workplace Size - < 10 (%)	21.6	31.8	15.0	17.4
Workplace Size - 10-49 (%)	31.0	35.3	26.4	28.5
Workplace Size - 50-499 (%)	33.2	25.5	36.7	35.4
Workplace Size - ≥ 500 (%)	14.3	7.3	22.0	18.7
Born Abroad (%)	11.9	14.9	8.2	10.3
Public Sector (%)	20.1	22.8	24.1	23.7
Permanent Contract (%)	80.9	65.8	94.9	91.8
Share of Part-Time (%)	28.0	-	11.2	14.5
Paid Hours Worked (Full-Time)	36.1	-	36.2	36.2

Note: This table presents summary statistics by group of preferences on working hours. Groups are considered based on their answers to the following questions in the surveys: *"do you ideally want to work* [more/less] *hours in your job with a corresponding income variation?"*. "Constrained from above" workers report that they ideally want to work more hours ; "Involuntary part-time" workers are the subsample of the previous group who currently work part-time but would ideally work full-time based on their desired hours ; "Constrained from below" workers report that they ideally want to work less hours ; "Unconstrained" workers answer no to both questions. "Occupation" categories correspond to the 1st-digit in the PCS classification, respectively 3, 4, 5 and 6. "Workplace Size" groups correspond to the number of salaried workers employed in the workplace. "Born Abroad" indicates the proportion of individuals born outside of France. "Public Sector" shows the proportion of workers in the public sector. "Permanent Contract" represents the share of workers with a permanent contract (*contrat à durée indéterminée*). Restricting to the EEC-DADS sample, the final row reports average paid hours worked of workers with full-time contracts.

Table A4: Event-Study Effects on Hours, Wages and Earnings - Voluntary Moves

Group (EEC Period):	Part-Time			Full-Time		
Dependent Variable (in logs):	Hours (1)	Wages (2)	Earnings (3)	Hours (4)	Wages (5)	Earnings (6)
Mover	0.059***	-0.023**	0.037***	0.015***	-0.023***	-0.008**
	(0.012)	(0.007)	(0.012)	(0.002)	(0.002)	(0.003)
Mover × Constrained	0.094***	-0.030*	0.064**	0.005	-0.003	0.001
	(0.026)	(0.013)	(0.025)	(0.006)	(0.004)	(0.006)
Fixed effects						
Worker FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
Baseline (in levels)	25.4	13.8	18,341	34.6	16.5	29,595
Observations	57,439	57,439	57,439	466,261	466,261	466,261
Adj. R^2	0.80	0.90	0.89	0.61	0.93	0.91

Signif. Codes: ***: 0.001, **: 0.01, *: 0.05.

Note: This table presents estimates from event-study regressions specified in equation 5 using the alternative definition of employer-to-employer moves similar to Babet and Chabaud (2024). The data used is the EEC-DADS Panel between 2003 and 2023 (see Section 3.3 for details). The sample is restricted to moves from a permanent contract with an unemployment period of less than 60 days between jobs. See Table 4 for details.

Table A5: Event-Study Effects on Hours, Wages and Earnings - Stable Constrained Workers

Group (EEC Period):	Part-Time			Full-Time		
Dependent Variable (in logs):	Hours (1)	Wages (2)	Earnings (3)	Hours (4)	Wages (5)	Earnings (6)
Mover	0.024**	-0.040***	-0.016	-0.002	-0.046***	-0.048***
	(0.009)	(0.004)	(0.009)	(0.002)	(0.001)	(0.002)
Mover × Constrained	0.043**	-0.005	0.039*	0.016***	0.005	0.021***
	(0.017)	(0.008)	(0.025)	(0.005)	(0.004)	(0.005)
Fixed effects						
Worker FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
Baseline (in levels)	25.4	13.9	18,438	34.6	16.6	29,782
Observations	56,125	56,125	56,125	455,484	455,484	455,484
Adj. R^2	0.78	0.89	0.88	0.60	0.93	0.90

Signif. Codes: ***: 0.001, **: 0.01, *: 0.05.

Note: This table presents estimates from event-study regressions specified in equation 5 using an alternative definition of constrained workers with stable preferences over their EEC period. The data used is the EEC-DADS Panel between 2003 and 2023 (see Section 3.3 for details). The sample of constrained workers is restricted to those whose preferences remain identical throughout their EEC period. See Table 4 for details.

Table A6: Event-Study Effects on Hours, Wages and Earnings - Specific Periods

Group (EEC Period):	Part-Time			Full-Time		
Dependent Variable (in logs):	Hours (1)	Wages (2)	Earnings (3)	Hours (4)	Wages (5)	Earnings (6)
Panel A: 2009-2023						
Mover	0.025**	-0.039***	-0.014	-0.001	-0.046***	-0.047***
	(0.009)	(0.004)	(0.009)	(0.002)	(0.001)	(0.002)
Mover × Constrained	0.065***	-0.008	0.057***	0.007	0.004	0.011*
	(0.015)	(0.007)	(0.015)	(0.004)	(0.003)	(0.005)
Panel B: 2003-2008, 2014-2023						
Mover	0.035***	-0.046***	-0.011	0.003	-0.048***	-0.045***
	(0.010)	(0.005)	(0.010)	(0.002)	(0.002)	(0.002)
Mover × Constrained	0.056**	-0.002	0.054**	0.003	0.003	0.006
	(0.017)	(0.008)	(0.017)	(0.005)	(0.004)	(0.005)
Panel C: 2003-2013, 2019-2023						
Mover	0.040***	-0.045***	-0.005	0.003	-0.048***	-0.045***
	(0.012)	(0.006)	(0.012)	(0.002)	(0.002)	(0.003)
Mover × Constrained	0.064**	-0.002	0.062**	0.009	0.003	0.012*
	(0.021)	(0.008)	(0.020)	(0.006)	(0.004)	(0.006)
Panel D: 2003-2018						
Mover	0.002	-0.030***	-0.028*	-0.015***	-0.041***	-0.056***
	(0.012)	(0.006)	(0.012)	(0.002)	(0.002)	(0.003)
Mover × Constrained	0.066**	-0.020*	0.046*	0.011	0.005	0.016**
	(0.021)	(0.009)	(0.021)	(0.006)	(0.004)	(0.006)
Fixed effects						
Worker FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X

Observations - Part-Time: A = 59,102 ; B = 46,769; C = 37,665; D = 37,706.
Observations - Full-Time: A = 469,357 ; B = 356,885 ; C = 310,121; D = 313,447.

Signif. Codes: ***: 0.001, **: 0.01, *: 0.05.

Note: This table presents estimates from event-study regressions specified in equation 5 using using four subsamples, each excluding a different five-year period. The data used is the EEC-DADS Panel between 2003 and 2023 (see Section 3.3 for details). See Table 4 for details.

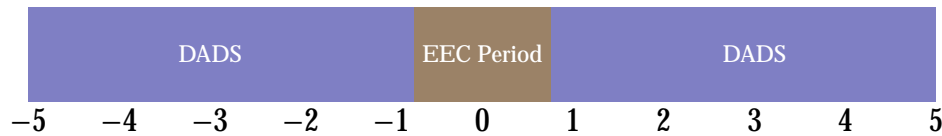Table A7: Event-Study Effects on Hours, Wages and Earnings - Reduced Distance to Work

Group (EEC Period):	Part-Time			Full-Time		
Dependent Variable (in logs):	Hours	Wages	Earnings	Hours	Wages	Earnings
	(1)	(2)	(3)	(4)	(5)	(6)
Mover	0.045***	-0.039***	0.006	-0.001	-0.041***	-0.042***
	(0.010)	(0.005)	(0.010)	(0.002)	(0.002)	(0.003)
Mover × Constrained	0.047**	-0.009	0.038*	0.005	0.002	0.007
	(0.018)	(0.009)	(0.018)	(0.005)	(0.004)	(0.005)
Fixed effects						
Worker FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
Baseline (in levels)	25.5	13.8	18,424	34.6	16.5	29,555
Observations	56,684	56,684	56,684	457,988	457,988	457,988
Adj. R^2	0.78	0.89	0.88	0.60	0.93	0.90

Signif. Codes: ***: 0.001, **: 0.01, *: 0.05.

Note: This table presents estimates from event-study regressions specified in equation 5 after restricting the sample to moves that increase the distance to commute by more than 10 kilometers. The data used is the EEC-DADS Panel between 2003 and 2023 (see Section 3.3 for details). Distances between municipalities are calculated using the Haversine formula, which computes the great-circle distance between two points on a sphere given their latitude and longitude coordinates. See Table 4 for details.
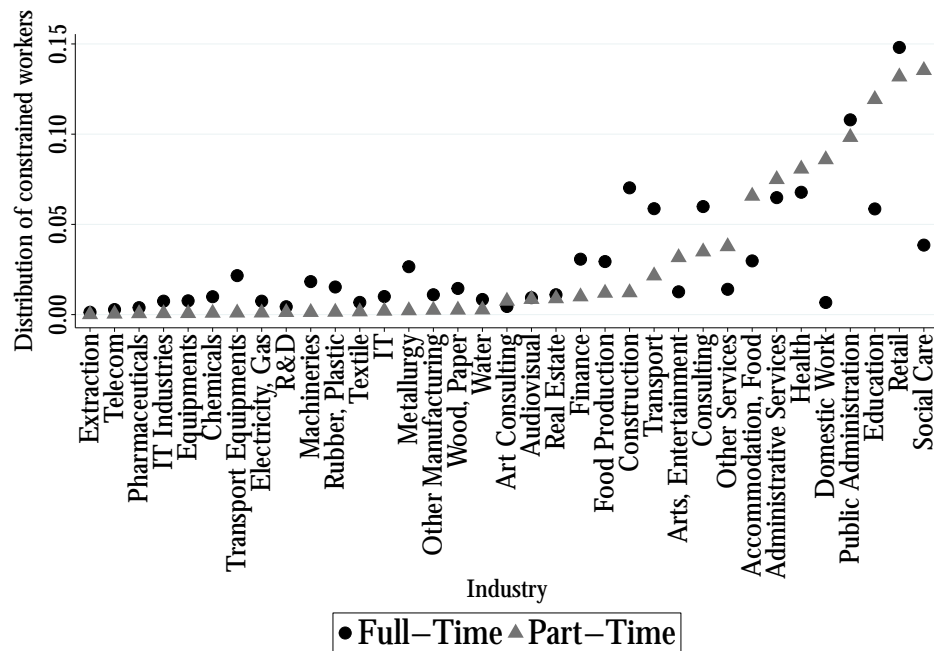
A.2 Figures

Figure A1: EEC-DADS Panel Data

DADS	EEC Period	DADS

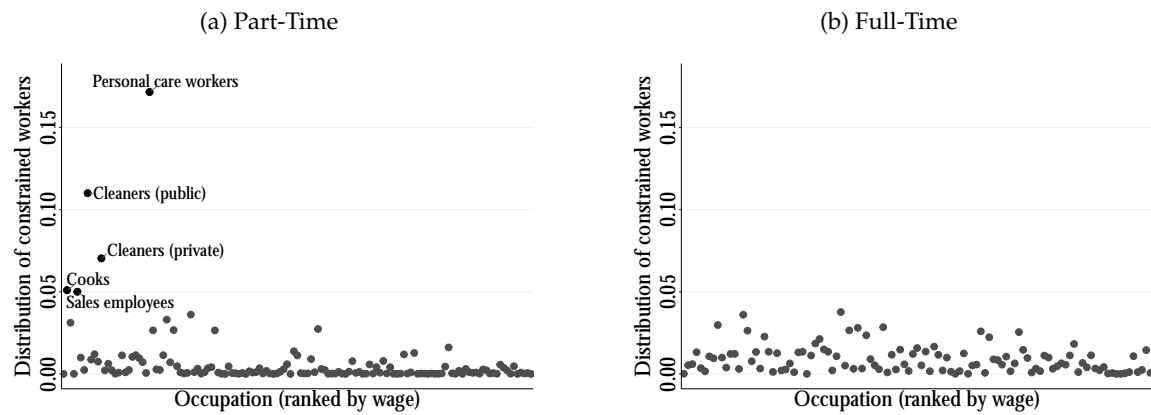| −5 | −4 | −3 | −2 | −1 | 0 | 1 | 2 | 3 | 4 | 5 |

Note: This figure illustrates the structure of the newly built EEC-DADS panel data. This dataset is constructed based on the EEC-DADS dataset and the DADS panel from Godechot et al. (2023). It combines for each individual EEC-based information over 6 quarters of observation (the EEC period) and DADS-based information over the period of appearance in the panel. See Section 3.3 for more details.

Figure A2: Distribution of Constrained Workers by Industry

Note: The figure shows the distribution of constrained (from above) workers across industries by working time status. Data is based on Labour Force Surveys pooled between 2003 and 2023. Each point corresponds to an industry from the NAF classification (38 levels). The y-axis indicates the proportion of the population constrained from above that works in a given industry.

Figure A3: Distribution of Constrained Workers by Occupation
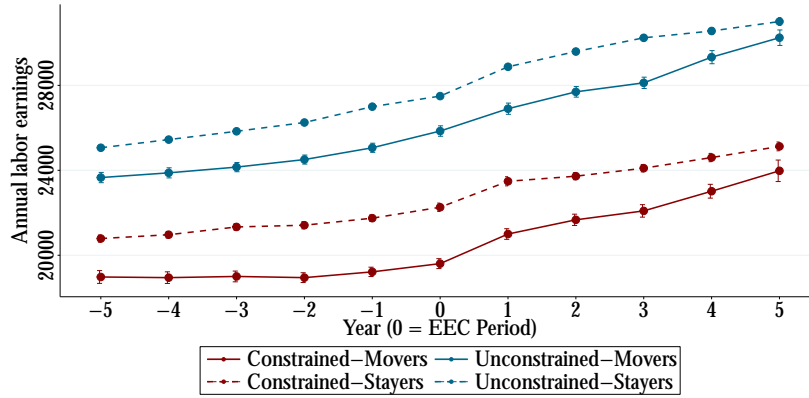
(a) Part-Time

(b) Full-Time

Note: The figures show the distributions of constrained (from above) workers across occupations by working time status. Data is based on Labour Force Surveys pooled between 2003 and 2023. Each bar corresponds to an occupation (ranked by wage) at the 3-digit level in the PCS classification (110 values). The y-axis indicates the proportion of the population constrained from above that works in a given occupation. An individual is constrained from above if he or she answers yes to the question: *"do you ideally want to work more hours in your job with a corresponding income variation?"* in the Labour Force Survey.

Figure A4: Mean Hours of Job Movers By Quartile

(a) Hours

(b) Wages

Note: These figures show mean hours (a) and hourly wages (b) of workers observed in 2003-2023 who change jobs and held the preceding job for 2 or more years, and the new job for 2 or more years, as in Card et al. (2013). The data used is the EEC-DADS Panel (see Section 3.3 for details). Here, the job refers to the establishment with most earnings during a given year. Each job is classified into quartiles based on mean hours or wages of co-workers (quartiles are based on all full time workers in the same year).

Figure A5: Evolution of Earnings in the EEC-DADS Panel

Note: This figure represents the evolution of earnings across employer-to-employer transitions for different worker groups. The x-axis shows years relative to the EEC period, while the y-axis displays average annual earnings. The data used is the EEC-DADS Panel (see Section 3.3 for details). Four distinct groups are tracked: constrained-movers (solid red line), unconstrained-movers (solid blue line), constrained-stayers (dashed red line), and unconstrained-stayers (dashed blue line). Workers are classified as constrained or unconstrained based on their reported hour preferences, and as movers or stayers based on whether they switch employers during years 1 to 3 after the observation period. Error bars correspond to 95% heteroskedasticity-robust confidence intervals.

Figure A6: Event-Study of Employer-to-Employer Moves on Hours Worked

(a) Mover
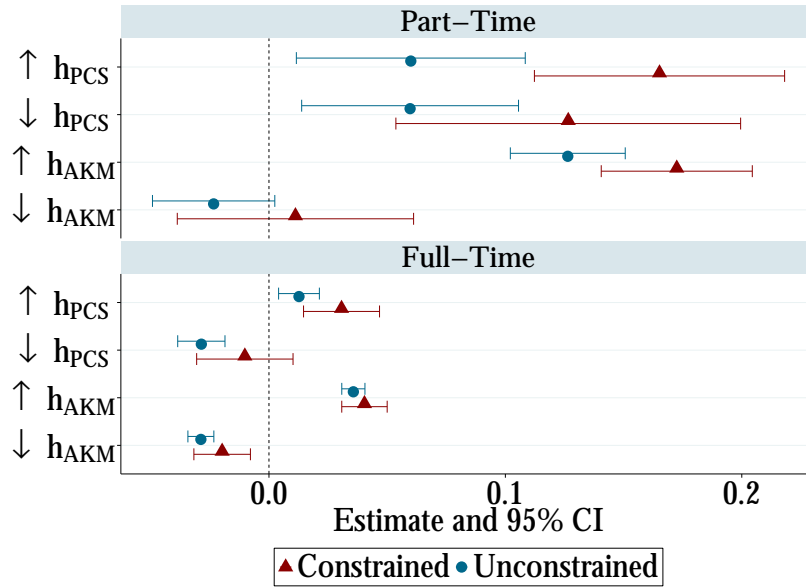
(b) Mover × Constrained

Note: Panel (a) shows event-study coefficients for the effect of employer-to-employer moves on weekly hours worked, following Callaway and Sant'Anna (2021), using never-treated individuals (non-movers) as control group. Panel (b) displays the interaction coefficients testing for differential move effects between constrained and unconstrained workers. Year 0 corresponds to the year of the employer-to-employer move. Point estimates are shown with 95% confidence intervals. Standard errors are clustered at the individual level.

Figure A7: Event-Study Effects by Type of Workers

Note: This figure shows event-study estimates on hours worked for constrained (red triangles) and unconstrained (blue circles) workers by type of worker. The data used is the EEC-DADS Panel (see Section 3.3 for details). The specification differs from Equation 5 (and Table 4) as the interaction term is excluded and separate regressions are run on the move dummy variable (S_{it} in Equation 5) for constrained and unconstrained workers. In each case, the group of non-movers is composed of both constrained and uncostrained workers. Occupations respectively correspond to the 1st-digit 3, 4, 5 and 6 in the PCS classification.

Figure A8: Event-Study Effects by Type of Mobility

Note: This figure shows event-study estimates on hours worked for constrained (red triangles) and unconstrained (blue circles) workers by type of mobility. The data used is the EEC-DADS Panel (see Section 3.3 for details). The specification differs from Equation 5 (and Table 4) as the interaction term is excluded and separate regressions are run for constrained and unconstrained workers to estimate β_1. See Table 4 for details about the variable used for mobility. The sample of movers is alternatively restricted to specific types of mobility. The first two rows show estimates for between-occupation movers split by whether they move to an occupation with more ($\uparrow h_{PCS}$) or fewer ($\downarrow h_{PCS}$) hours than their origin occupation. The last two rows show estimates for all movers (both within-occupation and between-occupation) split by whether they move to a firm with a higher ($\uparrow h_{AKM}$) or lower ($\uparrow h_{AKM}$) AKM firm effect on hours than their origin firm. The estimation of AKM firm effects is detailed in Section 4.2. Non-movers serve as the comparison group for all estimates. Error bars correspond to 95% heteroskedasticity-robust confidence intervals.

Appendix B   Measurement Issues and Data Linkage

B.1   Survey Measurement of Hours Constraints

This section provides additional background validation checks to the Labour Force Survey variables used to measure hours constraints. The paper relies on a certain interpretation of workers' answers to the corresponding questions. I argue that positive answers to the STPLC question reveal a concrete and thoughtful preference for working additional hours.

Methods to Increase Hours.   Workers who report constraints from above and are available to work more hours are asked in a follow-up question (CSTPLC) about their preferred method to increase their hours with a list of possible items. 75% of these workers wish to work longer in their current job, while only 5% would rather take an additional job, 6% would opt to change jobs entirely, and 14% would do so by any means. The fact that a large majority of workers consider increasing their hours in their current working context supports the interpretation of the measure as embedded in real life context. Workers who are constrained from above thus do not appear to answer the question from a utopian perspective.

Motivations.   Additional information from the EEC allows to evaluate the consistency of workers' reports with their motivations. Figure B1a shows the answers to the question *"What is the main reason you work part-time?"* (RAISTP), asked to part-time workers. Almost every involuntary part-time worker, who represent 75% of constrained (from above) part-time workers, reports being primarily limited by the absence of full-time jobs. On the other hand, part-time workers who do not wish to work longer hours typically cite personal factors like family reasons or free time as their main motivation for part-time work. The gap in that dimension between both types of workers is consistent with the measurement of constraints. Surprisingly, a non-negligible share of unconstrained workers, 20%, also report the unavailability of full-time contracts as their motivation for part-time work. This suggests a possible underestimation of the share of involuntary part-time workers. I adopt a similar approach with a question regarding motivations for another job (CREACCP). Focusing on the period between 2013 and 2023 (because of a break in series in 2013), I analyze answers to the question *"Why do you want another job?"* asked to workers who report that they want another job (either in replacement or in addition to the current one), with multiple possible answers in a list of items. Figure B1b shows that reports of a higher ideal number
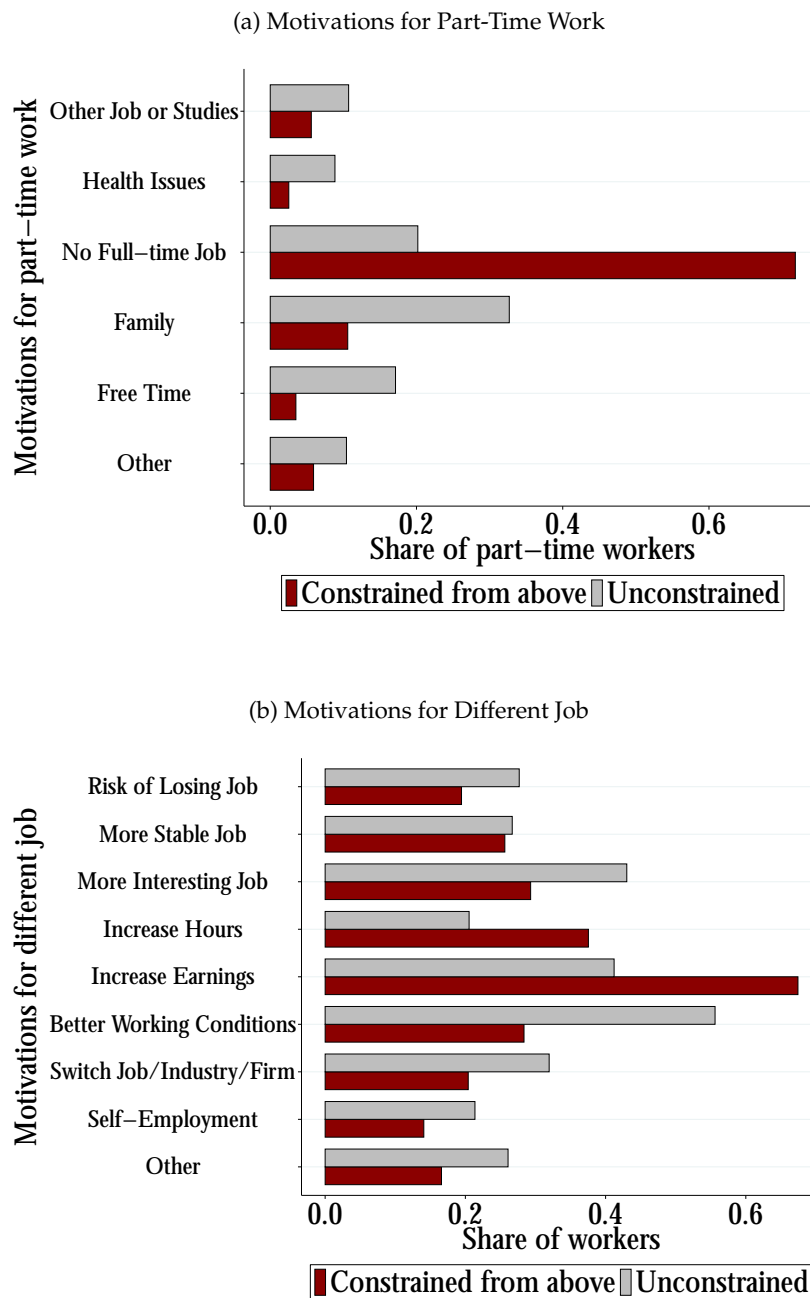
of hours are associated with prospects of increased earnings and hours. Beyond the consistency of both variables, this illustrates that the desire to work long hours is likely strongly motivated by the perspective of higher earnings. Positive answers to the STPLC question thus convey ambition for a higher income at the cost of additional hours. This interpretation makes the measurement of hours constraints through the STPLC question coherent with traditional labor supply models and sets the stage for a welfare analysis of hours constraints.

Persistence of Hours Preferences. An important question lies in understanding the stability of hours preferences over time. Individuals surveyed in the EEC are asked to report their preferences during 6 consecutive quarters at most which allows me to measure the persistence of STPLC over this period. I find that 63% of individuals who report constraints from above during their last interrogation, a definition that I use throughout Section 5, also report the same type of constraints in their first interrogation. This proportion marginally increases to 70% when only considering part-time workers but remains quite low. Additional checks suggest that the instability of preferences is not driven by changes in the employment context (employer, occupation, contract, hours worked) of the individual. This aspect of the variable is a potential threat to the results in Sections 5 and 6 which extrapolate preferences on hours over the years following the EEC period. To address this issue, I provide a robustness check in Section 5.5 where I change my definition of constrained individuals to workers who report constraints both at their first and last interrogation in the EEC period. The main conclusions of the paper remain valid.

Worker Mobility. Figure B2 exploits the quarterly longitudinal structure of the EEC to examine the connection between reported preferences for hours and employer-to-employer mobility. Workers who report an ideal number of hours superior to their current one on their first interrogation switch employers significantly more than both unconstrained workers and workers who would ideally reduce their hours[27]. Half of individuals who move report being unconstrained in their last interrogation. This finding suggests that positive answers to the STPLC question are associated with workplace disutility, hence with mobility towards alternative employers. As a result, it reinforces the interpretation of questions regarding ideal working hours as indicative of hours constraints faced by workers.

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[27]The result is robust to the introduction of controls on age, gender and occupation.

Figure B1: Motivations of Constrained and Unconstrained Workers

(a) Motivations for Part-Time Work
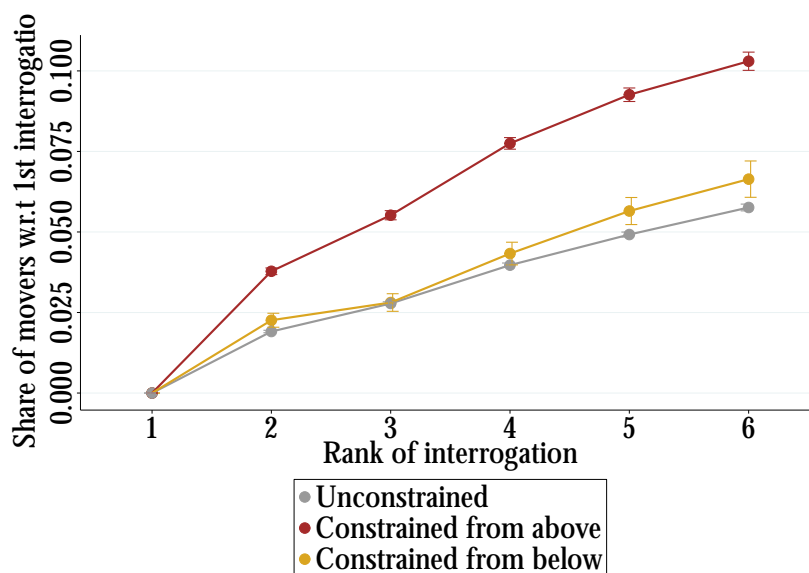

(b) Motivations for Different Job

Note: These figures represent the motivations of workers to work as part-time or to look for a different job based on their constraint status in the labor market. Workers are classified as *constrained from above* or *unconstrained* based on their answer to the STPLC question in the Labour Force Survey. See 3.1 for more details.

(a) The figure reports answers to the question *"What is the main reason you work part-time?"* asked to part-time workers in the Labour Force Survey. The sample covers 144,904 workers between 2003 and 2023.

(b) The figure shows answers to the question *"Why do you want another job?"* asked to workers who report that they want another job (either in replacement or in addition to the current one) in the Labour Force Survey. Multiple answers are possible. The sample covers 94,573 workers between 2013 and 2023. The period is restricted to 2013-2023 for this question only in order to ensure the consistency of the variable across the years.

Figure B2: Worker Mobility in the EEC

Note: This figure represents worker mobility patterns across quarterly rounds of interrogation in the Labour Force Survey. Workers are classified as unconstrained, top-constrained, or bottom-constrained based on their answer to the STPLC question during their first interrogation. See 3.1 for more details. The x-axis shows the rank of interrogation while the y-axis displays the share of workers who are not in the same workplace *(SIRET)* as in their first interrogation. The sample covers 717,544 workers between 2003 and 2023.

Transitions Between Constrained and Unconstrained Status. Table B1 also exploits the quarterly longitudinal structure of the EEC to examine the relationship between changes in stated hours preferences and actual labor market outcomes. Panels A and B respectively focus on workers constrained from above or unconstrained in their first interrogation. The first column of the table corresponds to the status reported in the last interrogation. Panel A shows that workers who switch from constrained to unconstrained over the EEC period experience a substantial increase in both hours and earnings compared to those who remain constrained throughout. Notably, workers who shift from being constrained from above to wanting fewer hours display even larger increases in usual hours. Panel B presents the mirror pattern: workers initially unconstrained who become constrained from above experience significant reductions in hours and earnings, while those maintaining their unconstrained status do not. Taken together, the patterns provide additional evidence for the validity of the hours preferences measure, as reported constraints correlate closely with subsequent changes in workers' labor market trajectories.

Distribution of Desired Hours. Figures B3a and B3b show the distributions of desired hours, as compared to actual hours, respectively for part-time and full-time constrained workers. Figure B3a shows a clear jump in desired hours around 35 hours for part-time workers, indicating
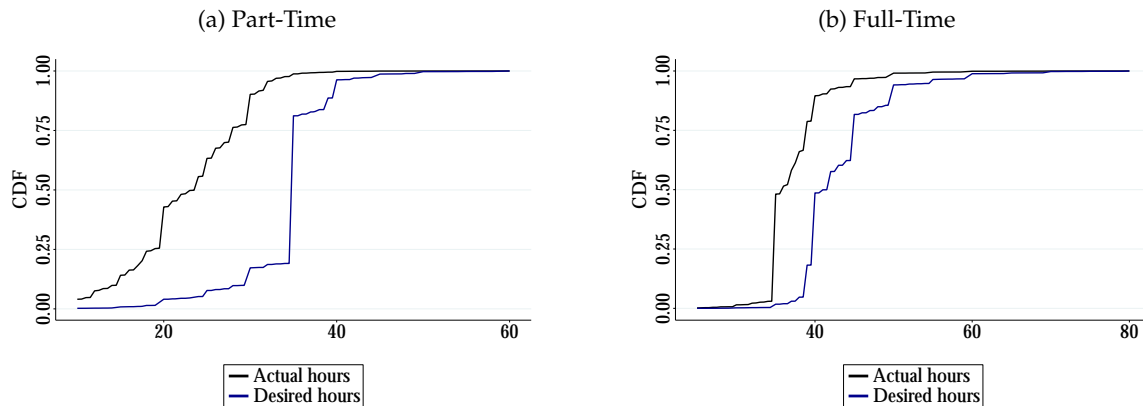
Panel A: Constrained from above in 1st interrogation

Period	Usual hours			Reference hours			Earnings			N
	First	*Last*	Δ	*First*	*Last*	Δ	*First*	*Last*	Δ	
Constrained from above	30.1	30.3	(+0.7%)	28.0	28.0	(+0.0%)	1,288	1,305	(+1.3%)	61,322
Constrained from below	34.5	37.3	(+8.1%)	31.5	31.7	(+0.6%)	1,565	1,702	(+8.8%)	918
Unconstrained	33.3	34.8	(+4.5%)	30.6	31.7	(+3.6%)	1,496	1,572	(+5.1%)	66,479

Panel B: Unconstrained in 1st interrogation

Period	Usual hours			Reference hours			Earnings			N
	First	*Last*	Δ	*First*	*Last*	Δ	*First*	*Last*	Δ	
Constrained from above	34.6	33.0	(-4.6%)	32.1	30.4	(-5.3%)	1,523	1,491	(-2.1%)	38,050
Constrained from below	41.1	41.5	(+1.0%)	37.5	36.4	(-2.9%)	2,237	2,277	(+1.8%)	8,010
Unconstrained	38.4	38.4	(+0.0%)	35.4	34.8	(-1.6%)	1,932	1,934	(+0.1%)	434,168

Note: This table presents changes in hours and earnings across changes in hours preferences based on Labour Force Surveys pooled between 2003 and 2023. Labels in the first column correspond to the worker's status in their last interrogation. Panel A restricts the sample to workers who report wanting to work more in their first interrogation. Panel B restricts the sample to workers who report not wanting to work more nor less in their first interrogation. Reference hours correspond to hours worked during the reference week of the Labour Force Survey. Earnings correspond to net monthly labor earnings.

that many constrained part-time workers want to move to full-time status. This suggests significant involuntary part-time employment among workers who cannot achieve their desired hours. Reassuringly, both panels show substantial variation in desired hours rather than excessive clustering at round numbers, e.g. like 40. This suggests that workers are genuinely reporting their true preferences rather than simply picking salient thresholds and lends credibility to the desired hours measure as capturing meaningful heterogeneity in workers' preferences.

Figure B3: Distribution of Actual and Desired Hours, EEC 2003-2023

(a) Part-Time

(b) Full-Time

Note: The figures show the distributions of actual and desired hours worked for constrained workers based on Labour Force Surveys pooled between 2003 and 2023. The sample has been restricted to constrained employees with hours worked above 10 and an hourly wage between 0.8 and 1000 times the hourly minimum wage.

B.2 Measurement of Hours Worked in French Administrative Data

This section aims to assess the reliability of working hours reported in the French matched employer-employee data (DADS). Those administrative datasets cover almost the entire salaried workforce and have been widely used in labor market studies. Reporting hours in the DADS is mandatory and the information is used to manage and administer unemployment insurance and social benefits. To check the validity of hours, I rely on the methodology of Lachowska et al. (2022), applied to the administrative data of the State of Washington, and extend it by incorporating elements specific to the French context. This methodology has become a standard procedure to evaluate the quality of hours data (see e.g. Labanca and Pozzoli (2022)).

As in the original paper, I first compare the distributions of hours worked in the administrative data and the Labour Force Survey, including on a common sample of workers. Although the definitions of hours worked differ according to the sources, this comparison highlights the degree of reliability of the variable according to the type of situation. Second, I measure the correlation between the evolution of annual earnings and hours worked for individuals who remain in the same job over two successive years of data, denoted as the "signal-to-noise" ratio in Lachowska et al. (2022). Assuming that their hourly wage should remain constant over time, the estimated coefficient should be relatively close to 1 (0.8 in the original paper). Third, I examine to what extent the lower end of the hourly wage distribution follows the evolution of the hourly minimum wage (the *Smic* in France) over time.

B.2.1 Hours Distributions in Admin and Survey Data

The first part compares the working hours distributions reported in the DADS and the Labour Force Survey, which is the main source of survey data for working time studies. I consider data for the years 2005, 2010, 2015, and 2019, covering the entire study period (2003-2023) while maintaining a manageable dataset size. Some restrictions are applied to the DADS data to limit measurement errors: workers aged between 18 and 64, in ordinary jobs of more than 120 hours and 60 days. I also keep one observation per person-year, the one with highest annual earnings to maintain consistency with the EEC definition of working hours *in the primary job*. Despite these adjustments, the comparison exercise has notable limitations.

First, the definition of hours worked is not the same across sources. The DADS data records the total number of paid hours for a given employer over the year. This definition is closer to
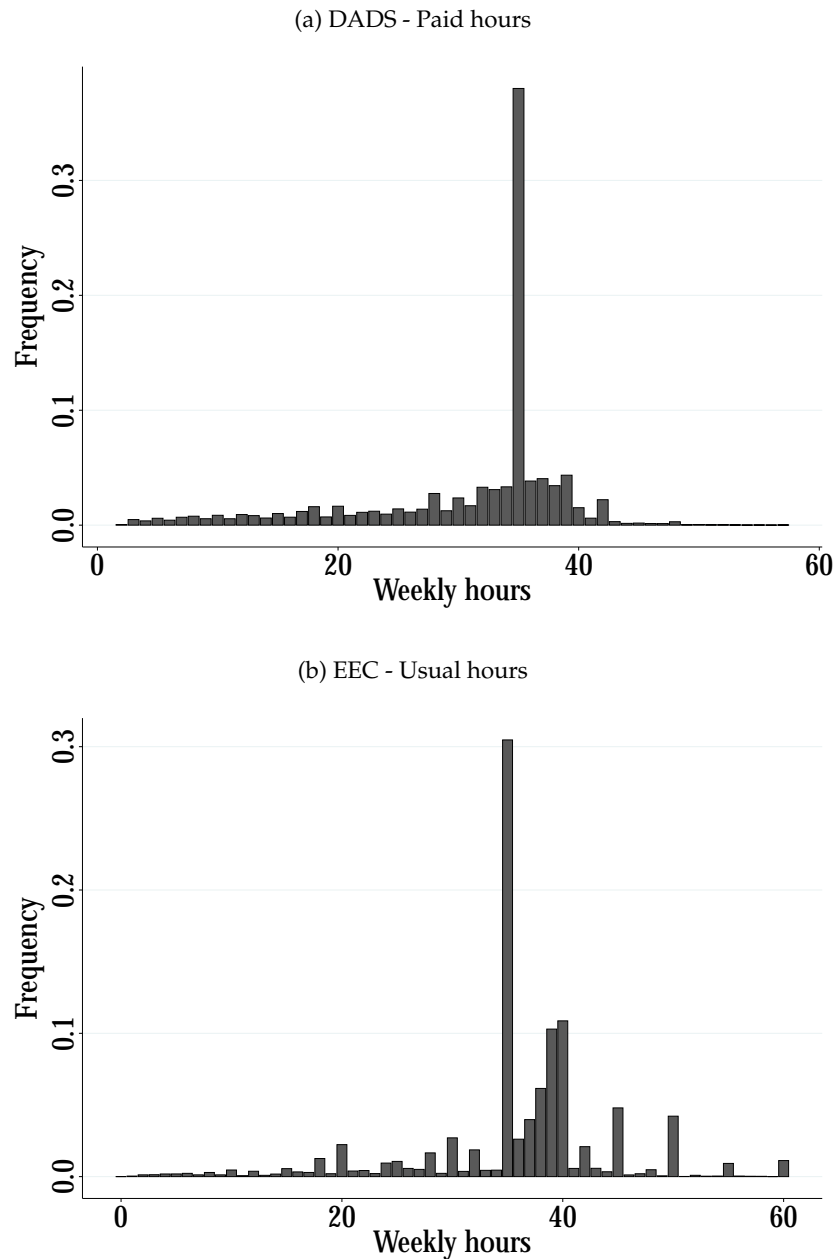
contractual working time including standard hours, overtime, and paid absences. The EEC data, on the other hand, asks individuals about their *usual* hours worked (including overtime) per week. In short, the EEC aims to estimate the actual working time of the individual, including times that do not necessarily result in remuneration, while the DADS reflects the employer's perspective on the official hours of their employees. Annual hours from the DADS are recomputed as weekly hours using the starting and ending dates of employment. Second, the scope of the two sources differs. The DADS provides information on all salaried workers, while the EEC draws its sample from all individuals living in ordinary housing, including inactive or non-salaried individuals. I retain only salaried workers in this sample, although they are not representative of the entire population. To address potential sampling issues, I also provide distributions of both types of hours from the common EEC-DADS sample introduced in Section 3.3.

Figures B4a and B4b show the distributions of hours respectively from the DADS and the EEC. It is clear that the 35-hour peak, the standard duration in France, is more pronounced in administrative data, compensated by an over-representation of declarations between 37 and 45 hours in the EEC. Figure B5 compares both distributions in the common EEC-DADS sample. The profiles are very close to the original figures which suggests that the gap in hours is not driven by representativeness issues. Figure B6 represents average DADS paid hours at each level of EEC usual hours. Values are very close to the $x = y$ line in the part-time space (below 35) while in the full-time case both measures show very limited correlation.

Two particularities of the French working time regulation system can help to explain the difference. First, *forfait jours* contracts are a French flexible work arrangement which entails that working time is measured in terms of annual working days rather than in weekly hours. For workers subject to this arrangement, about 15% of the workforce in 2019, the employer is not required to monitor hours worked, nor to report them in their DADS record. The absence of hours worked is circumvented by Insee through recoding to an arbitrary number of hours. Since 2017, a variable of the DADS dataset (UNITMESUREREF) allows to identify workers with a forfait jours contract. They turn out to be mainly attributed either 1820 or 2200 annual hours depending on the year of data. Forfait jours contracts are excluded from the sample in the majority of the paper and their removal is made explicit. Second, the gap in hours distributions between DADS and EEC could also be due to the *Réduction du Temps de Travail* (RTT) scheme. This arrangement grants rest days or half-days to an employee if the working time exceeds 35 hours per week (up to 39 hours weekly). Then, an employee who has a contract with 39 hours per week would probably report
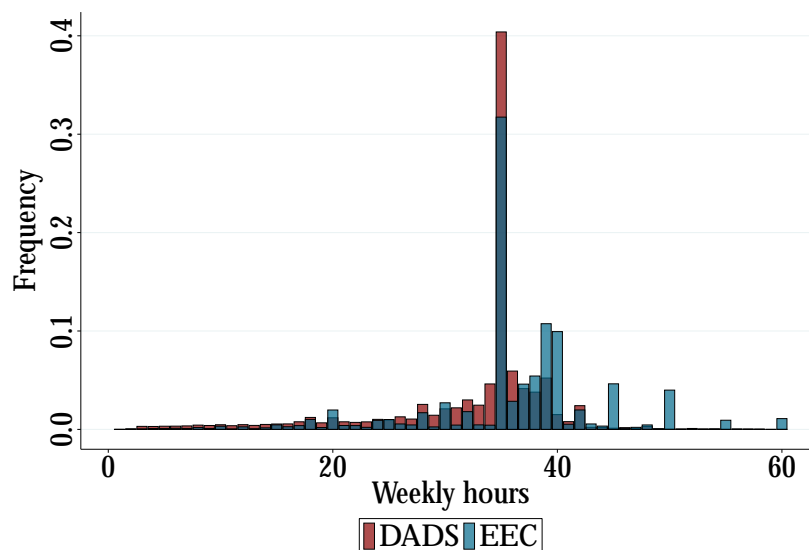
39 usual hours in the EEC but their total number of hours over the year would correspond to a 35-hour equivalent. Apart from those two mechanisms, the gap in hours may reflect that workers on the right-side of the graph tend to over-report their hours.

Figure B4: Distributions of Weekly Hours, EEC vs DADS, 2005, 2010, 2015 and 2019

(a) DADS - Paid hours
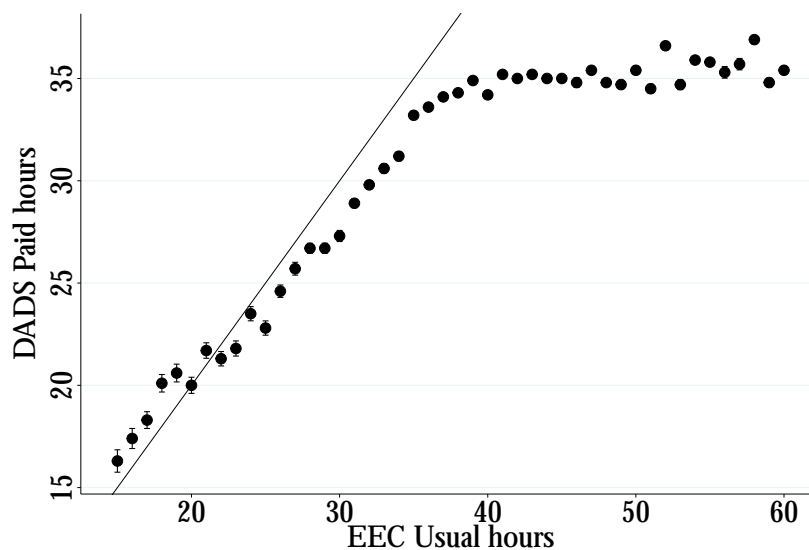

(b) EEC - Usual hours

Note: These figures show the distributions of weekly working hours in the DADS and the French Labour Force Survey (EEC) in years 2005, 2010, 2015 and 2019. The sample includes salaried workers aged 15-64 in ordinary jobs of more than 120 hours and 60 days. Annual paid hours from the DADS are recomputed as full-year equivalent using the employment duration and then divided by 52 and rounded to obtain weekly hours. Values above 60 are not displayed.

Figure B5: Distributions of Weekly Hours, EEC-DADS

Note: This figure shows the distributions of weekly working hours in the EEC-DADS dataset between 2003 and 2023. The sample includes salaried workers aged 15-64 in ordinary jobs of more than 120 hours and 60 days. Annual paid hours from the DADS are recomputed as full-year equivalent using the employment duration and then divided by 52 and rounded to obtain weekly hours. Values above 60 are not displayed.

Figure B6: Comparison of Hours Worked, EEC-DADS

Note: This figure shows the relation between DADS paid hours and EEC usual hours in the EEC-DADS dataset between 2003 and 2023. Values correspond to the average of DADS paid hours at each (rounded) level of EEC usual hours. The diagonal line has slope 1. The sample includes salaried workers aged 15-64 in ordinary jobs of more than 120 hours and 60 days. Annual paid hours from the DADS are recomputed as full-year equivalent using the employment duration and then divided by 52 and rounded to obtain weekly hours. EEC weekly hours below 15 and above 60 are not displayed. Error bars correspond to the coefficient of variation.

B.2.2 Signal-to-Noise Regressions

The hourly wage of a worker paid through an hours contract can be considered to fluctuate stochastically around a fixed hourly rate. This observation from Lachowska et al. (2022) suggests that a simple regression of the evolution of annual labor earnings in logs between two periods $[\Delta \ln(earn_{it})]$ on the equivalent change in terms of hours worked $[\Delta \ln(hrs_{it})]$ provides a test of the reliability of the measurement of hours:

$$\Delta \ln(earn_{it}) = \alpha + \beta \Delta \ln(hrs_{it}) + \varepsilon_{it}$$

The test is not as relevant in the DADS yearly data as it is in the original Washington state quarterly data because hourly wages are more likely to increase e.g. due to promotion. Still, if hours are measured accurately, the estimates of the coefficient on the evolution of hours (β) should be arbitrarily close to 1 for hourly paid workers. On the other hand, if hours are measured with significant error, the coefficient from this simple regression is expected to be *attenuated*. Using the DADS yearly files between 2018 and 2019, I retain workers who stay in the same company and the same occupation across years and estimate the coefficient β in different specifications.

Table B2: Signal-to-Noise Coefficients between Earnings and Hours, 2018-2019

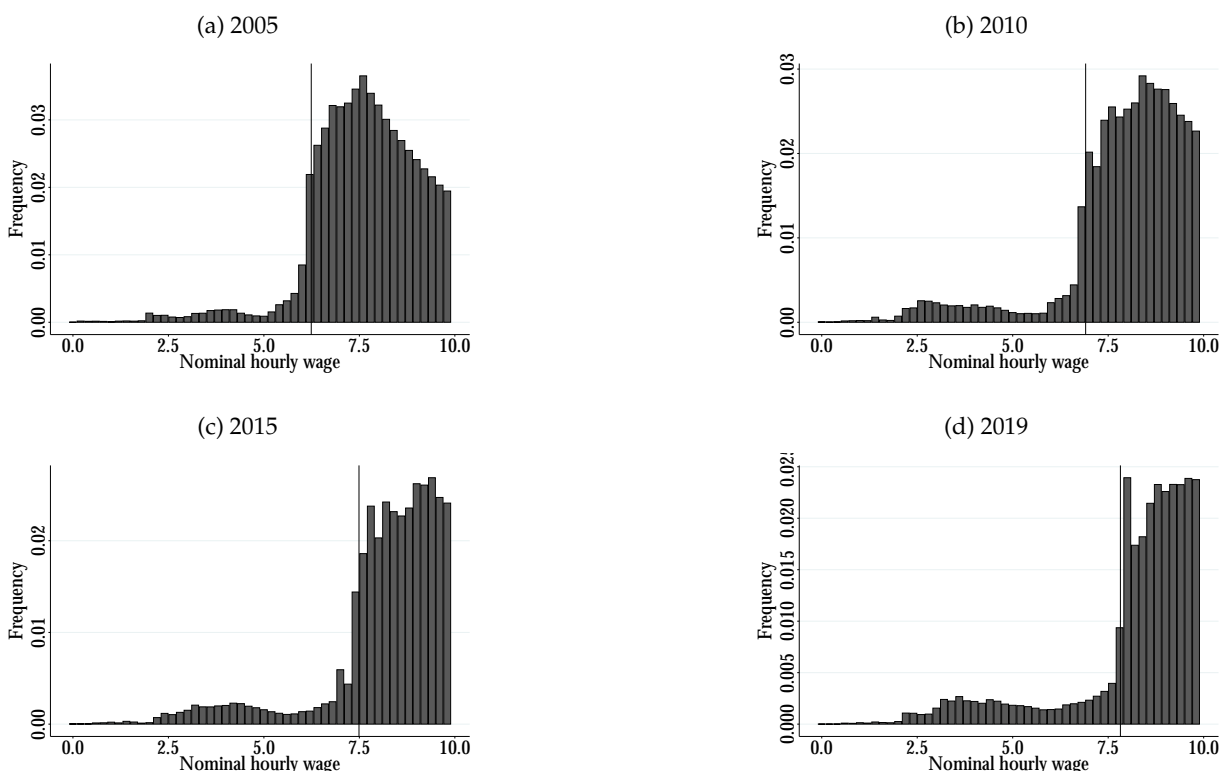| Dependent variable:	$\Delta \ln(earn_{it})$			
	(1)	(2)	(3)	(4)
$\Delta \ln(hrs_{it})$	0.684	0.684	0.692	0.692
	(0.000)	(0.001)	(0.002)	(0.001)
Employer FE	No	No	Yes	Yes
Std. Errors	Standard	Clustered at worker level	Standard	Clustered at worker level
Observations	12,608,316	12,608,316	12,608,316	12,608,316
Adj. R^2	0.49	0.49	0.62	0.62

Note: This table shows the results of the signal-to-noise regression using different specifications. The sample is composed of workers from the DADS 2018 annual dataset who stay with the same primary employer and the same occupation in 2019. Standard errors are in parentheses.

The results show a coefficient slightly below 0.7 stable across specifications. Complementary results by industry show strong homogeneity in signal-to-noise coefficients. Lachowska et al. (2023) consider that a coefficient equal to 0.8, in an area with 63% hourly-paid workers indicates low measurement error in hours. The lower proportion of hourly-paid workers in France coupled with the yearly nature of the data partly explain the lower coefficient and suggest that the DADS data could have a measurement quality similar to Washington state data.

B.2.3 Minimum Wage Changes and Nominal Wage Distributions

A simple test of the reliability of working hours, at least for low-wage employees, is to observe whether the distribution of nominal hourly wages reflects the variations in the net hourly minimum wage (the *Smic horaire*) over time. The hourly minimum wage is indexed to the inflation rate measured for workers below the first quintile of the earnings distribution. Figure B7 presents the results for 2005, 2010, 2015, and 2019. The distribution of hourly wages exhibits a shift in the concentration of wages over time that corresponds to variations in the net hourly minimum wage. This pattern would not be observable in a database with significant measurement error. In particular, this exercise rules out systematic, time-invariant reporting.

Figure B7: Distribution of Hourly Wages and Minimum Wage

Note: These figures represent the distributions of nominal hourly wages around the net hourly minimum wage (the *Smic horaire*) in 2005, 2010, 2015 and 2019. Nominal hourly wages are obtained by dividing net annual earnings by the annual number of hours worked in the DADS. Black vertical lines correspond to the net hourly minimum wage for the respective year. The values for the hourly minimum wage (in current euros) are 6.24 (a), 6.91 (b), 7.49 (c) and 7.82 (d). Distributions are divided into intervals of 0.20 euros and values above 10 euros are not displayed.

B.3 Matching EEC and DADS

This section describes the procedure for linking the French Labour Force Survey (EEC) with the French matched employer-employee dataset (DADS) at the individual level. The general approach consists of finding the individuals surveyed by the EEC in the DADS exhaustive records. The sample only includes perfectly identified individuals i.e. who appear in a 1-to-1 match. This sample is then connected to the DADS panel obtained by following the procedure of Godechot et al. (2023). This ultimately leads to an innovative EEC-DADS Panel combining 6 quarters of observation in the EEC with the worker's employment history.

The challenge of matching the French Labour Force Survey with the DADS lies in the absence of a common individual identifier. However, both datasets share a number of variables that are supposed to be consistent: age, sex, occupation, part-time/full-time work, birth department, birth month (only between 2009 and 2012), residence municipality, and establishment's ID (*SIRET*). Table B3 reports the names of the variables. The *SIRET* is the key variable that makes this match feasible, as it considerably reduces the number of individuals with the same characteristics and therefore limits the risk of "1-to-many" matches. Age (at the end of the year) and sex are never missing and have no reason to differ across sources for a given individual. The combination of these three variables is the base of the matching procedure and already provides a strong identifier, as "1-to-many" matches would only occur if there are at least two individuals of the same age and gender who work in the same workplace during the same year. Other variables are more subject to misreporting and are thus at some point recoded or removed from the list of matching variables. The idea is to use all common variables to build a correspondence table between individual identifiers of both sources for each year. Importantly, the EEC information concerns the primary job of the employee, which means that the linkage is realized through this employment spell. But, once an individual has been matched and appears in the correspondence table, all their employment spells during the year can be recovered from the DADS.

The procedure starts with some minor cleaning of the EEC to make some variables consistent with their DADS equivalent. All quarterly files between 2003 and 2023 are pooled, restricting the sample to employees whose *SIRET* information is not missing - about 81% of the sample (see Table A1). Likewise, the regional DADS files are pooled to build yearly DADS datasets with the minimum required number of variables (the individual ID *IDENT_S* and the matching variables). The match is then performed in multiple steps with different subsets of the set of matching vari-

Table B3: Variables for EEC-DADS Matching

Variable	EEC	DADS	Description
Establishment's ID	SIRET	SIRET	The SIRET is a unique identifier for establishments in France. In the EEC, the variable is coded by Insee based on the establishment's adress reported by the individual. In the DADS, it is directly reported by HR services.
Age	AG	AGE	Age of the individual at the end of the year.
Sex	SEXE	SEXE	Gender of the individual (male/female classification).
Occupation	CSTOT, P	CS, PCS	The French occupational classification system changed in 2008. 2-digit variables are used prior to 2009 (CSTOT in the EEC and CS in the DADS), while the 4-digit current system variables (P in the EEC and PCS in the DADS) are used afterwards.
Working Time Status	TPPRED	CPFD	Employment status (full-time or part-time).
Birth County	DNAI	DEP_NAISS	French *département* (101 values) where the individual was born.
Birth Month (2009-2012)	NAIM	MOIS_NAISSANCE	Month of birth, available only for the specified period in the DADS.
Municipality of Residence	DEPCOM	COMR	French municipality, identified by the *Code commune*, where the individual resides.

Note: This table contains the names and description of variables used to link the EEC and DADS datasets. Variable names correspond to the 2019 version of each dataset (except for occupation and birth month). Multiple revisions between 2003 and 2023 have induced changes in the names and content of several variables. These changes are taken into account in the cleaning process in order to build a version consistent over the years.

ables in order to optimize "1-to-1" matches. Here are the 11 sets of variables used through the procedure (using the DADS labels reported in Table B3):

- **Set 1:** SIRET, AGE, SEXE, PCS, CPFD, DEP_NAISS, COMR

- **Set 2:** SIRET, AGE, SEXE, PCS, CPFD, COMR

- **Set 3:** SIRET, AGE, SEXE, PCS, CPFD, DEP_NAISS

- **Set 4:** SIRET, AGE, SEXE, CPFD, DEP_NAISS, COMR

- **Set 5:** SIRET, AGE, SEXE, CS, CPFD, DEP_NAISS, COMR

- **Set 6:** SIRET, AGE, SEXE, CS, CPFD, COMR

- **Set 7:** SIRET, AGE, SEXE, CS, CPFD, DEP_NAISS

- **Set 8:** SIRET, AGE, SEXE, CS 1st digit, DEP_NAISS, COMR

- **Set 9:** SIRET, AGE, SEXE, CPFD, DEP_NAISS

- **Set 10:** SIRET, AGE, SEXE, DEP_NAISS

- **Set 11 (2009-2012):** SIRET, AGE, SEXE, MOIS_NAISSANCE

The match is run with a R script called `2_eecdads_id.R` at the yearly level using clean and appended EEC and DADS files. At each step, I remove from both datasets individuals who have already been matched in order to avoid double matching. The complete process yields a correspondence table for each year between unique identifiers from the EEC (*IDENT* $\times$ *NOI*) and the DADS (*IDENT_S*). Using the correspondence table, one can retrieve all observations of identified individuals in the EEC and the DADS yearly files to build the EEC-DADS sample.

Appendix C   Theory

C.1   Extended Lewis-Rosen Model Proofs

Bargained Wage Components.   We compute the derivative of w_{ij}^b with respect to α_i. Starting from Equation 3, we have:

$$
\frac{\partial w_{ij}^b}{\partial \alpha_i} = \frac{\frac{\partial R_j}{\partial \alpha_i} h_{ij}^b - \frac{\partial h_{ij}^b}{\partial \alpha_i} R_j(h_{ij}^b, \alpha_i)}{(h_{ij}^b)^2} \left[1 - \frac{k_j(\alpha_i)}{R_j(h_{ij}^b, \alpha_i)} \right] - \frac{R_j(h_{ij}^b, \alpha_i)}{h_{ij}^b} \left[\frac{k_j'(\alpha_i) R_j(h_{ij}^b, \alpha_i) - \frac{\partial R_j}{\partial \alpha_i} k_j(\alpha_i)}{R_j(h_{ij}^b, \alpha_i)^2} \right]
$$

$$
= \left[\frac{1}{h_{ij}^b} \frac{\partial R_j}{\partial \alpha_i} - \frac{\partial h_{ij}^b}{\partial \alpha_i} \frac{R_j(h_{ij}^b, \alpha_i)}{(h_{ij}^b)^2} \right] \left[1 - \frac{k_j(\alpha_i)}{R_j(h_{ij}^b, \alpha_i)} \right] - \frac{1}{h_{ij}^b} \left[\frac{k_j'(\alpha_i) R_j(h_{ij}^b, \alpha_i) - \frac{\partial R_j}{\partial \alpha_i} k_j(\alpha_i)}{R_j(h_{ij}^b, \alpha_i)} \right]
$$

$$
= \frac{1}{h_{ij}^b} \frac{\partial R_j}{\partial \alpha_i} \left[1 - \frac{k_j(\alpha_i)}{R_j(h_{ij}^b, \alpha_i)} + \frac{k_j(\alpha_i)}{R_j(h_{ij}^b, \alpha_i)} \right] - \frac{1}{h_{ij}^b} \frac{\partial h_{ij}^b}{\partial \alpha_i} \frac{R_j(h_{ij}^b, \alpha_i)}{h_{ij}^b} \left[1 - \frac{k_j(\alpha_i)}{R_j(h_{ij}^b, \alpha_i)} \right] - \frac{1}{h_{ij}^b} k_j'(\alpha_i)
$$

$$
= \frac{1}{h_{ij}^b} \left[\frac{\partial R_j(h_{ij}^b, \alpha_i)}{\partial \alpha_i} - \frac{\partial h_{ij}^b}{\partial \alpha_i} w_{ij}^b - \frac{\partial k_j(\alpha_i)}{\partial \alpha_i} \right].
$$

C.2   Alternative Definitions of Willingness-To-Pay

Here, I compare the main definition of willingness-to-pay (WTP) introduced in Section 6 with the definition from Lachowska et al. (2023). In particular, I show that the latter is always superior to the former in the case where an individual who is constrained from above.

For simplicity, denote $u_0 = u(h_0, w_0)$ and $u^* = u(h^*, w_0)$, the two levels of utility that drive the estimation. Starting from the functional form of worker utility, for a given utility level u and hours h, the hourly wage is:

$$
w = \frac{u + \varepsilon h^\mu}{h}
$$

Using this expression, both definitions of the WTP can be rewritten as:

$$
\theta = w_0 - w(u_0, h^*) = \frac{u^* + \varepsilon h^{*\mu}}{h^*} - \frac{u_0 + \varepsilon h^{*\mu}}{h^*} = \frac{u^* - u_0}{h^*}
$$

$$
\theta_{alt} = w(u^*, h_0) - w_0 = \frac{u^* + \varepsilon h_0^\mu}{h_0} - \frac{u_0 + \varepsilon h_0^\mu}{h_0} = \frac{u^* - u_0}{h_0}
$$

In the case where the individual is constrained from above, h_0 is lower than h^*, by definition. Hence, $\theta_{alt} > \theta$ is always true for a given constrained worker.